231791

STATE OF SOUTH CAROLINA

(Caption of Case)

Application of Carolina Water Service, Incorporated for Approval of an Increase in Its Rates for Water and Sewer Services Provided to All of Its Service Areas in South Carolina

BEFORE THE PUBLIC SERVICE COMMISSION OF SOUTH CAROLINA

COVER SHEET

DOCKET/NDI NUMBER: 2011 - 47 - WS

(Please type or print)
Submitted by: Scott Elliott

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NOTE: The cover sheet and information contained herein neither replaces nor supplements the filing and service of pleadings or other papers as required by law. This form is required for use by the Public Service Commission of South Carolina for the purpose of docketing and must be filled out completely.

DOCKETING INFORMATION (Check all that apply)

☐ **Emergency Relief demanded in petition**

☐ **Request for item to be placed on Commission's Agenda expeditiously**

☐ **Other:**

INDUSTRY (Check one)	NATURE OF ACTION (Check all that apply)		
☐ Electric	☐ Affidavit	☐ Letter	☐ Request
☐ Electric/Gas	☐ Agreement	☐ Memorandum	☐ Request for Certification
☐ Electric/Telecommunications	☐ Answer	☐ Motion	☐ Request for Investigation
☐ Electric/Water	☐ Appellate Review	☐ Objection	☐ Resale Agreement
☐ Electric/Water/Telecom.	☐ Application	☐ Petition	☐ Resale Amendment
☐ Electric/Water/Sewer	☐ Brief	☐ Petition for Reconsideration	☐ Reservation Letter
☐ Gas	☐ Certificate	☐ Petition for Rulemaking	☐ Response
☐ Railroad	☐ Comments	☐ Petition for Rule to Show Cause	☐ Response to Discovery
☐ Sewer	☐ Complaint	☐ Petition to Intervene	☐ Return to Petition
☐ Telecommunications	☐ Consent Order	☐ Petition to Intervene Out of Time	☐ Stipulation
☐ Transportation	☐ Discovery	☐ Prefiled Testimony	☐ Subpoena
☐ Water	☐ Exhibit	☐ Promotion	☐ Tariff
☒ Water/Sewer	☐ Expedited Consideration	☐ Proposed Order	☐ Other:
☐ Administrative Matter	☐ Interconnection Agreement	☐ Protest	
☐ Other:	☐ Interconnection Amendment	☐ Publisher's Affidavit	
	☐ Late-Filed Exhibit	☐ Report	

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August 29, 2011

VIA E FILING
Jocelyn Boyd, Esquire
Chief Clerk and Administrator
SC Public Service Commission
P. O. Drawer 11649
Columbia, SC 29211

RE: Application of Carolina Water Service, Inc. for adjustment of Rates and Charges and Modification of Certain Terms and Conditions for the Provision of Water and Sewer Service
DOCKET NO.: 2011-47-WS

Dear Ms. Boyd:

Enclosed please find Schedules PMA15 –PMA 21 to the exhibit to the rebuttal testimony of Pauline M. Ahern. Regrettably, Schedules PMA16- PMA21 were inadvertently omitted from the filing of last week. Separately, I have served a copy of Schedules PMA15-PMA 21 on all parties of record electronically and by mail.

If you or your staff has questions, please do not hesitate to contact me.

Sincerely,

Elliott & Elliott, P.A.

Scott Elliott

SE/jcl

Enclosures

cc: All Parties of Record w/enc.

Carolina Water Service, Inc.
Docket No. 2011-47-WS

BEFORE THE

PUBLIC SERVICE COMMISSION OF SOUTH CAROLINA

EXHIBIT

TO ACCOMPANY THE

PREPARED REBUTTAL TESTIMONY

OF

PAULINE M. AHERN, CRRA
PRINCIPAL
AUS CONSULTANTS

ON BEHALF OF

CAROLINA WATER SERVICE, INC.

CONCERNING

FAIR RATE OF RETURN

AUGUST 2011

Do Analyst Conflicts Matter? Evidence from Stock Recommendations

Anup Agrawal *University of Alabama*
Mark A. Chen *Georgia State University*

Abstract

We examine whether conflicts of interest with investment banking and brokerage businesses induce sell-side analysts to issue optimistic stock recommendations and, if so, whether investors are misled by such biases. Using quantitative measures of potential conflicts constructed from a novel data set containing revenue breakdowns of analyst employers, we find that recommendation levels are indeed positively related to conflict magnitudes. The optimistic bias stemming from investment banking conflicts was especially pronounced during the late-1990s stock market bubble. However, evidence from the response of stock prices and trading volumes to upgrades and downgrades suggests that the market recognizes analysts' conflicts and properly discounts analysts' opinions. This pattern persists even during the bubble period. Moreover, the 1-year stock performance following revised recommendations is unrelated to the magnitude of conflicts. Overall, our findings do not support the view that conflicted analysts are able to systematically mislead investors with optimistic stock recommendations.

1. Introduction

In April 2003, 10 of the largest Wall Street firms reached a landmark settlement with state and federal securities regulators on the issue of conflicts of interest

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faced by stock analysts.[1] The settlement requires the firms to pay a record $1.4 billion in compensation and penalties in response to government charges that the firms issued optimistic stock research to win favor with potential investment banking (IB) clients. Part of the settlement funds are earmarked for investor education and for provision of research from independent firms. In addition to requiring large monetary payments, the settlement mandates structural changes in the firms' research operations and requires the firms to disclose conflicts of interest in analysts' research reports.

The notion that investors are victims of biased stock research presumes that (1) analysts respond to the conflicts by inflating their stock recommendations and (2) investors take analysts' recommendations at face value. Even if analysts are biased, it is possible that investors understand the conflicts of interest inherent in stock research and rationally discount analysts' opinions. This alternative viewpoint, if accurate, would lead to very different conclusions about the consequences of analysts' research. Indeed, investors' rationality and self-interested behavior imply that stock prices should accurately reflect a consensus about the informational quality of public announcements (Grossman 1976; Grossman and Stiglitz 1980). Rational investors would recognize and adjust for analysts' potential conflicts of interest and thereby largely avoid the adverse consequences of biased stock recommendations.

In this article, we provide evidence on the extent to which analysts and investors respond to conflicts of interest in stock research. We address four questions. First, is the extent of optimism in stock recommendations related to the magnitudes of analysts' conflicts of interest? Second, to what extent do investors discount the opinions of more conflicted analysts? In particular, do stock prices and trading volumes react to recommendation revisions in a manner that rationally reflects the degree of analysts' conflicts? Third, is the medium-term (that is, 3- to 12-month) performance of recommendation revisions related to conflict severity? And, finally, did conflicts of interest affect analysts or investors differently during the late-1990s stock bubble than during the postbubble period? The answers to these questions are clearly of relevance to stock market participants, public policy makers, regulators, and the academic profession.

We use a unique, hand-collected data set that contains the annual revenue breakdown for 232 public and private analyst employers. This information allows us to construct quantitative measures of the magnitude of potential conflicts not only from IB business but also from brokerage business. We analyze a sample of over 110,000 stock recommendations issued by over 4,000 analysts during the 1994–2003 time period. Using univariate tests as well as cross-sectional regressions that control for the size of the company followed and individual analysts' experience, resources, workloads, and reputations, we attempt to shed

[1] Two more securities firms (Deutsche Bank Securities Inc. and Thomas Weisel Partners LLC) were added to the formal settlement in August 2004.

light both on how analysts respond to pressures from IB and brokerage businesses and on how investors compensate for the existence of such conflicts of interest.

A number of studies (for example, Dugar and Nathan 1995; Lin and McNichols 1998; Michaely and Womack 1999; Dechow, Hutton, and Sloan 2000; Bradley, Jordan, and Ritter 2008) focus on conflicts faced by analysts in the context of existing underwriting relationships (see also Malmendier and Shanthikumar 2007; Cliff 2007).[2] Our article complements this literature in several ways. First, we take into account the pressure to generate underwriting business from both current and potential client companies. Even if an analyst's firm does not currently do IB business with a company that the analyst tracks, it might like to do so in the future. Second, we examine the conflict between research and all IB services (including advice on mergers, restructuring, and corporate control), rather than just underwriting. Third, we examine conflicts arising from brokerage business in addition to those from IB.[3]

Fourth, the prior empirical finding that underwriter analysts tend to be more optimistic than other analysts is consistent with two alternative interpretations: (*a*) an optimistic report on a company by an underwriter analyst is a reward for past IB business or an attempt to win future IB business by currying favor with the company or (*b*) a company chooses an underwriter whose analyst already likes the stock. The second interpretation implies that underwriter choice is endogenous and does not necessarily imply a conflict of interest. We sidestep this issue of endogeneity by not focusing on underwriting relations between an analyst's firm and the company followed. Instead, our conflict measures focus on the importance to the analyst's firm of IB and brokerage businesses, as measured by the percentage of its annual revenue derived from IB business and from brokerage commissions. Unlike underwriting relations between an analyst's firm and the company followed, the proportions of the entire firm's revenues from each of these businesses can reasonably be viewed as given, exogenous variables from the viewpoint of an individual analyst. Finally, our approach yields substantially larger sample sizes than those used in prior research, and it therefore leads to greater statistical reliability of the results.

Several articles adopt an approach that is similar in spirit to ours. For example, Barber, Lehavy, and Trueman (2007) find that recommendation upgrades (downgrades) by investment banks—which typically also have brokerage businesses—

[2] Bolton, Freixas, and Shapiro (2007) theoretically analyze a different type of conflict of interest in financial intermediation, one faced by a financial advisor whose firm also produces financial products (such as in-house mutual funds). Mehran and Stulz (2007) provide an excellent review of the literature on conflicts of interest in financial institutions.

[3] Hayes (1998) analyzes how pressure on analysts to generate brokerage commissions affects the availability and accuracy of earnings forecasts. Both Irvine (2004) and Jackson (2005) find that analysts' optimism increases a brokerage firm's share of the trading volume. Ljungqvist et al. (2007) find that analysts employed by larger brokerage houses issue more optimistic recommendations and more accurate earnings forecasts. However, none of these articles examines how investors' responses to analysts' recommendations and the investment performance of recommendations vary with the severity of brokerage conflicts, issues that we investigate here.

underperform (outperform) similar recommendations by non-IB brokerages and independent research firms. Cowen, Groysberg, and Healy (2006) find that full-service securities firms—which have both IB and brokerage businesses—issue less optimistic forecasts and recommendations than do non-IB brokerage houses. Finally, Jacob, Rock, and Weber (2008) find that short-term earnings forecasts made by investment banks are more accurate and less optimistic than those made by independent research firms. We extend this line of research by quantifying the reliance of a securities firm on IB and brokerage businesses. This is an important feature of our article for at least two reasons. First, given that many securities firms operate in multiple lines of business, it is difficult to classify them by business lines. By separately measuring the magnitudes of both IB and brokerage conflicts in each firm, our approach avoids the need to rely on a classification scheme. Second, since the focus of this research is on the consequences of analysts' conflicts, the measurement of those conflicts is important. Our conclusions sometimes differ from those in classification-based studies.

We find that analysts do indeed seem to respond to pressures from IB and brokerage businesses: larger potential conflicts of interest from these businesses are associated with more positive stock recommendations. We also document that the distortive effects of IB conflicts were larger during the late-1990s stock bubble than during the postbubble period. Nonetheless, the empirical analysis yields several pieces of evidence to suggest that investors are sophisticated enough to adjust for these biases. First, the short-term reactions of both stock prices and trading volumes to recommendation upgrades are negatively and statistically significantly related to the magnitudes of potential IB or brokerage conflicts. For downgrades, the corresponding relation is negative for stock prices but positive for trading volumes. Second, the 1-year investment performance after recommendation revisions bears no systematic relation to the magnitude of conflicts. Finally, investors continued to discount conflicted analysts' opinions during the bubble period, even amid the euphoria prevailing in the market at the time. Together these results strongly support the idea that the marginal investor, taking analysts' conflicts into account, rationally discounts optimistic stock recommendations.[4]

The remainder of the article is organized as follows. We discuss the issues in Section 2 and describe our sample and data in Section 3. Section 4 examines the relation between recommendation levels and the degree of IB or brokerage conflict faced by analysts. Section 5 analyzes how conflicts are related to the response of stock prices or trading volumes to recommendation revisions. Section

[4] In a companion paper (Agrawal and Chen 2005), we find that analysts appear to respond to conflicts when making long-term earnings growth projections but not short-term earnings forecasts. This finding is consistent with the idea that, with short-term forecasts, analysts worry about their deception being revealed with the next quarterly earnings release, but they have greater leeway with long-term forecasts. We also find that the frequency of forecast revisions is positively related to the magnitude of brokerage conflicts, and several tests suggest that analysts' trade generation incentives impair the quality of stock research.

6 investigates the relation between conflicts and the investment performance of recommendation revisions. Section 7 presents our results for the late-1990s stock bubble and postbubble periods, and Section 8 concludes.

2. Issues and Hypotheses

Investment banking activity is a potential source of analyst conflict that has received widespread attention in the financial media (for example, Gasparino 2002; Maremont and Bray 2004) as well as the academic literature (for example, Lin and McNichols 1998; Michaely and Womack 1999). When IB business is an important source of revenue for a securities firm, a stock analyst employed by the firm often faces pressure to inflate his or her recommendations. This pressure is due to the fact that the firm would like to sell IB services to a company that the analyst tracks.[5] The company, in turn, would like the analyst to support its stock with a favorable opinion. Thus, we expect that the more critical is IB revenue to an analyst's employer, the greater the incentives an analyst faces to issue optimistic recommendations.[6]

Analysts also face a potential conflict with their employers' brokerage businesses. Here, the pressure on analysts originates not from the companies that they follow but from within their employing firms. Brokerage business generates a large portion of most securities firms' revenues, and analyst compensation schemes are typically related explicitly or implicitly to trading commissions. Thus, analysts have incentives to increase trading volumes in both directions (that is, buys and sells). Given the many institutional constraints that make short sales relatively costly, many more investors participate in stock purchases than in stock sales.[7] Indeed, it is mostly existing shareholders of a stock who sell. This asymmetry between purchases and sales implies that the more important brokerage business is to an analyst's employer, the more pressure the analyst faces to be bullish when issuing recommendations.

Analysts who respond to the conflicts they face by issuing blatantly misleading stock recommendations can develop bad reputations that reduce their labor income and hurt their careers.[8] Stock recommendations, however, are not as easily evaluated as other outputs of analysts' research, such as 12-month price targets or quarterly earnings forecasts, which can be judged against public, near-

[5] Throughout this article, we refer to an analyst's employer as a "firm" and a company followed by an analyst as a "company."

[6] Ljungqvist, Marston, and Wilhelm (2006, forthcoming) find that, while optimistic recommendations do not help the analyst's firm win the lead underwriter or comanager positions in general, they help the firm win the comanager position in deals in which the lead underwriter is a commercial bank.

[7] Numerous regulations in the United States increase the cost of selling shares short (see, for example, Dechow et al. 2001). Therefore, the vast majority of stock sales are regular sales rather than short sales. For example, over the 1994–2001 period, short sales comprised only about 10 percent of the annual New York Stock Exchange trading volume (New York Stock Exchange 2002).

[8] See Jackson (2005) for a theoretical model showing that analysts' concerns about their reputations can reduce optimistic biases arising from brokerage business.

term realizations. So it is not clear whether analysts' career concerns can completely prevent them from responding to pressures to generate IB or brokerage business.

The relation between conflict severity and the short-term (2- or 3-day) stock price impact of a recommendation should depend on whether investors react to the opinion rationally or naively.[9] Under the rational discounting hypothesis, the relation should be asymmetric for upgrades and downgrades. For upgrades, the stock price response should be negatively related to the degree of conflict. This implication arises because analysts who face greater pressure from IB or brokerage business are likely to be more bullish in their recommendations, and rational investors should discount an analyst's optimism more heavily. For downgrades, however, the story is different. When an analyst downgrades a stock despite facing large conflicts, rational investors should find the negative opinion more convincing and should be more likely to revalue the stock accordingly. This implies that the short-term stock price response to a downgrade should be negatively related to the degree of conflict.

The rational discounting hypothesis also predicts cross-sectional relations between conflict severity and the short-term trading volume responses to recommendations. As Kim and Verrecchia (1991) demonstrate in a rational expectations model of trading, the more precise a piece of news, the more individuals will revise their prior beliefs and, hence, the more trading that will result. In the present context, investor rationality implies that an upgrade by a highly conflicted analyst represents less precise news to investors, and so such a revision should be followed by a relatively small abnormal volume. But when an analyst downgrades a stock despite a substantial conflict, the signal is regarded as being more precise, and thus the downgrade should lead to relatively large abnormal trading.

By contrast, under the naive investor hypothesis, investors are largely ignorant of the distortive pressures that analysts face and accept analysts' recommendations at face value. This implies that there should be no relation between conflict severity and the short-term response of either stock prices or trading volume to recommendation revisions. Furthermore, the absence of a systematic relation should hold true for both upgrades and downgrades.

What are the implications of the two hypotheses for the medium-term (3- to 12-month) investment performance of analysts' recommendations? Under the rational discounting hypothesis, there should be no systematic relation between the magnitude of conflicts faced by an analyst and the performance of his or her stock recommendations: the market correctly anticipates the potential distortions up front and accordingly adjusts its response. But the naive investor hypothesis predicts that performance should be negatively related to conflict

[9] This framework follows Kroszner and Rajan (1994) and Gompers and Lerner (1999), who analyze the conflicts that a bank faces in underwriting securities of a company when the bank owns a (debt or equity) stake in it.

severity for both upgrades and downgrades. That is, investors ignore analysts' conflicts up front and pay for their ignorance later.

3. Sample and Data

3.1. Sample

Our sample of stock recommendations comes from the Institutional Brokers Estimate System (I/B/E/S) U.S. Detail Recommendations History file. This file contains data on newly issued recommendations as well as revisions and reiterations of existing recommendations made by individual analysts over the period 1993–2003. Although the exact wording of recommendations can vary considerably across brokerage houses, I/B/E/S classifies all recommendations into five categories ranging from strong buy to strong sell. We rely on the I/B/E/S classification and encode recommendations on a numerical scale from 5 (strong buy) to 1 (strong sell).

Since we are primarily interested in examining how the nature and consequences of analysts' recommendations are related to IB or brokerage business, we require measures of the importance of these business lines to analysts' employers. Under U.S. law, all registered broker-dealer firms must file audited annual financial statements with the Securities and Exchange Commission (SEC) in x-17a-5 filings.[10] These filings contain information on broker-dealer firms' principal sources of revenue, broken down into revenue from IB, brokerage commissions, and all other businesses (such as asset management and proprietary trading). We use these filings to obtain various financial data, including data on our key explanatory variables: the fractions of total brokerage house revenues from IB and from brokerage commissions. Beginning with the names of analyst employers contained in the I/B/E/S Broker Translation file,[11] we search for all available revenue information in x-17a-5 filings from 1994 to 2003.[12] For publicly traded broker-dealer firms, we also use 10-K annual report filings over the sample period to gather information on revenue breakdowns, if necessary. We thus obtain annual data from 1994 to 2003 on IB revenue, brokerage revenue, and other revenue for 188 privately held and 44 publicly traded brokerage houses.[13] For each brokerage house, we match recommendations to the latest broker-year revenue data preceding the recommendation date. Over the sample period, we

[10] The Securities Exchange Act, sections 17(a)–17(e), requires these filings. We accessed them from Thomson Financial's Global Access database and the Securities and Exchange Commission's (SEC's) public reading room in Washington, D.C.

[11] We use the file supplied directly by the Institutional Brokers Estimate System (I/B/E/S) on CD-ROM. This file does not recode the name of an acquired brokerage firm to that of its acquirer for years before the merger.

[12] The electronic availability of x-17a-5 filings is very limited prior to 1994, the year the SEC first mandated electronic form filing. Hence, we do not search for revenue information prior to 1994.

[13] We exclude a small number of firm-years in which the total revenue is negative (for example, because of losses from proprietary trading).

are able to match in this fashion 110,493 I/B/E/S recommendations issued by 4,089 analysts.

All broker-dealer firms are required to publicly disclose their balance sheets as part of their x-17a-5 filings. But a private broker-dealer firm can withhold the public disclosure of its income statement, which contains the revenue breakdown information needed for this study, if the SEC deems that such disclosure would harm the firm's competitive position. Thus, our sample of private securities firms is limited to broker-dealers that disclose their revenue breakdowns in x-17a-5 filings. We examine whether this selection bias affects our main results by separately analyzing the subsample of publicly traded securities firms, for which public disclosure of annual revenue information is mandatory. Our findings do not appear to be affected by this selection bias. All of our results for the subsample of publicly traded securities firms are qualitatively similar to the results for the full sample reported in the article. In the Appendix, we describe the characteristics of disclosing and nondisclosing private securities firms, shed some light on the firms' income statement disclosure decisions, and use a selectivity-corrected probit model to examine whether the resulting selection bias can explain analysts' response to conflicts in these private firms. We find no evidence that selection bias affects our results for these firms.

3.2. *Characteristics of Analysts, Their Employers, and Companies Followed*

We next measure characteristics of analysts, their employers, and the companies they cover. Prior research (for example, Clement 1999; Jacob, Lys, and Neale 1999) finds that analysts' experience and workloads affect the accuracy and credibility of their research. Using the I/B/E/S Detail History files, we measure an analyst's experience and workloads in terms of all research activity reported in I/B/E/S, including stock recommendations, quarterly and annual earnings-per-share forecasts, and long-term earnings growth forecasts. We measure general research experience as the number of days since an analyst first issued research on any company in the I/B/E/S database and company-specific research experience as the number of days since an analyst first issued research on a particular company. We measure an analyst's workload as the number of different companies or the number of different four-digit I/B/E/S sector industry groups (S/I/Gs)[14] for which the analyst issued research in a given calendar year.

The amount of resources devoted to investment research within brokerage houses also affects the quality of analysts' research (Clement 1999). Larger houses have access to better technology, information, and support staff. Accordingly, we use three measures of brokerage house size: the number of analysts issuing stock recommendations for a brokerage house over the course of a calendar year, book value of total assets, and net sales. All of our subsequent results are qual-

[14] The I/B/E/S sector industry group numbers are six-digit codes that provide information on the industry sectors and subsectors for companies in the I/B/E/S database. We use the first four digits, which correspond to broad industry groupings.

Table 1
Revenue Sources (%) of Analysts' Employers

Recommendation Level	Investment Banking Mean	Investment Banking Median	Brokerage Commission Mean	Brokerage Commission Median	Sample Size
5 (Strong buy)	13.94	11.81	29.87	24.09	28,901
4 (Buy)	13.81	11.21	26.68	17.22	37,478
3 (Hold)	12.68	11.13	28.44	24.07	37,883
2 (Sell)	11.61	10.55	23.13	16.12	4,875
1 (Strong sell)	16.27	14.90	33.44	24.95	1,356
p-Value (4 and 5) versus (1 and 2)	.0000	.0000	.0000	.0023	

Note. Shown are the percentages of analyst employer revenues from investment banking and brokerage commissions, by recommendation level. Data are for 110,493 stock recommendations and are drawn from the Institutional Brokers Estimate System U.S. Detail Recommendations History file for 1994–2003.

itatively similar under each of the three size measures. To save space, we report results only of tests based on the first size measure.

To capture the degree to which investors believe that individual analysts have skill in providing timely and accurate research, we use two measures of analysts' reputation. The first is based on *Institutional Investor* (*II*) magazine's All-America Research Team designation. Each year around October 15, *II* mails an issue to subscribers that lists the names of analysts who receive the most votes in a poll of institutional money managers. About 300–400 analysts are identified. We construct a variable that indicates, for each recommendation revision, whether the recommending analyst was named to the first, second, third, or honorable mention team in the latest annual survey. As a complementary, objective measure of analysts' reputation, we use a variable based on the *Wall Street Journal*'s (*WSJ*'s) annual All-Star Analysts Survey. The *WSJ* All-Star Analysts are determined by an explicit set of criteria relating to past stock-picking performance and forecasting accuracy.[15] The survey covers about 50 industries annually and names the top five stock pickers and top five earnings forecasters in each industry.[16]

Tables 1 and 2 report summary data on the characteristics of our sample. In Table 1, both the mean and the median percentages of analyst employer revenues derived from IB decline monotonically over the first four recommendation levels, but these values are the highest for strong sell recommendations. Similarly, it is the brokerage firms issuing strong sell recommendations that generally derive

[15] We recognize that the performance metrics used in the *Wall Street Journal* (*WSJ*) All-Star Analysts Survey are public information and can, in principle, be replicated by investors. However, to the extent that computing and evaluating analysts' performance is a costly activity, being named an All-Star Analyst can still affect an analyst's reputation and credibility.

[16] Since the I/B/E/S Broker Translation File provides only analysts' last names and first initials, in some instances it is not possible to ascertain from the I/B/E/S data alone whether an analyst in our sample was named to the *Institutional Investor* (*II*) or *WSJ* team. For these cases, we determine team membership of analysts from NASD BrokerCheck, an online database (http://www.nasd.com, accessed October 2004) that provides the full names of registered securities professionals as well as their employment and registration histories for the past 10 years. The database also keeps track of analysts' name changes (such as those resulting from marriage).

Table 2

Characteristics of Analysts, Firms, and Companies Followed

Characteristic	Mean	Median	SD	Sample Size
Investment banking revenue (%)	13.60	11.25	11.93	94,892
Brokerage commission revenue (%)	28.74	24.07	24.75	94,892
Analyst's company-specific experience (years)	2.42	1.20	3.29	85,531
Analyst's general experience (years)	6.41	4.90	5.32	85,531
Analysts employed by a firm	86.34	60	79.73	94,618
Companies followed by an analyst	17.24	15	12.93	84,016
Four-digit I/B/E/S S/I/Gs followed by an analyst	3.05	3	1.90	84,014
Institutional Investor All-America stock picker	.005	0	.07	85,531
Institutional Investor All-America Research Team member	.035	0	.18	85,531
Wall Street Journal All-Star stock picker	.018	0	.13	85,531
Wall Street Journal All-Star Analyst	.136	0	.34	85,531
Market capitalization ($ millions)	8,804.46	1,367.22	27,758.81	81,333
Analyst following	9.14	7	6.88	92,869

Note. Data are for 94,892 recommendation revisions and are drawn from the Institutional Brokers Estimate System (I/B/E/S) U.S. Detail Recommendations History file for 1994–2003. Recommendation revisions include recommendation changes as well as initiations, resumptions, and discontinuations of coverage. Analysts' experience is measured from all analyst research activity reported in I/B/E/S, including earnings-per-share forecasts, long-term earnings growth forecasts, and stock recommendations. An analyst is considered to be a top stock picker or team member if he or she appeared in the relevant portion of the most recent analyst survey by *Institutional Investor* or the *Wall Street Journal* at the time of a recommendation revision. Market capitalization is measured 12 months before the end of the current month, and analyst following is measured on the basis of stock recommendation coverage. Market capitalization values are inflation adjusted (with Consumer Price Index numbers and with 2003 as the base year). S/I/G = sector industry group.

the highest percentage of their total revenues from brokerage commissions. Notably, in each of the five categories, the mean percentage of revenue from commissions is about twice as large as the mean percentage of revenue from IB. This fact underscores the importance of trading commissions as a source of revenue for many securities firms. The last column shows that about 95 percent of the recommendations in the sample are at levels 5 (strong buy), 4 (buy), or 3 (hold). Levels 1 (strong sell) and 2 (sell) represent only about 1 percent and 4 percent of all recommendations, respectively.

The data in Table 2 provide a flavor of our sample of analysts and their employers. As noted by Hong, Kubik, and Solomon (2000), careers as analysts tend to be relatively short. The median recommendation is made by an analyst with under 5 years of experience, of which just over a year was spent following a given stock. Stock analysts tend to be highly specialized, following a handful of companies in a few industries. The median recommendation is made by an analyst following 15 companies in three industries who works for a securities firm employing 60 analysts. Being named as an All-America Research Team member by *II* is a rare honor, received by under 5 percent of all analysts in our sample. Finally, the typical company followed is large, with mean (median) market capitalization of about $8.8 billion ($1.4 billion) in inflation-adjusted

2003 dollars. Over the time span of a year, a company is tracked by a mean (median) of 9.1 (7) analysts.

4. Conflicts and the Levels of Analyst Recommendations Net of the Consensus

In this section, we examine whether the level of an analyst's stock recommendation net of the consensus (that is, median) recommendation level is related to the conflicts that he or she faces. We start by ascertaining the level of the outstanding recommendation on each stock by each analyst following it at the end of each quarter (March, June, September, December) from 1995 through 2003. An analyst's recommendation on a stock is included only if it is newly issued, reiterated, or revised in the preceding 12 months.

We estimate a regression explaining individual analysts' net stock recommendation levels at the end of a quarter (which is the recommendation level minus the median recommendation level across all analysts following a stock during the quarter).[17] The regression pools observations across analysts, stocks, and quarters and includes our two main explanatory variables: the percentage of an analyst employer's total revenues from IB and the percentage from brokerage commissions. Following Jegadeesh et al. (2004) and Kadan et al. (forthcoming), who find that momentum is an important determinant of analysts' recommendations, we control for the prior 6-month stock return.

The regression also controls for other factors that can affect the degree of analysts' optimism, such as the size of the company followed and the resources, reputation, experience, and workload of an analyst. As a measure of the resources available to an analyst, a dummy variable is used for a large brokerage house, and it equals one if the firm ranks in the top quartile of all houses in terms of the number of analysts employed during the year. The size of the company followed is measured by the natural logarithm of its market capitalization, measured 12 months before the end of the month. We measure an analyst's reputation by dummy variables that equal one if the recommending analyst was named in the most recent year as an All-America Research Team member by *II* or as an All-Star Analyst by the *WSJ*. An analyst's company-specific research experience is measured by the natural logarithm of one plus the number of days an analyst has been producing research (including earnings-per-share forecasts, long-term growth forecasts, or stock recommendations) on the company. We measure an analyst's workload by the natural logarithm of one plus the number of companies for which he or she produces forecasts or recommendations in the current year.

Finally, we control for industry and time period effects by adding dummy variables for I/B/E/S two-digit S/I/G industries and for each calendar quarter (March 1995, June 1995, and so forth). Since net recommendation levels can

[17] To ensure meaningful variation in the dependent variable, we omit stocks followed by only one analyst in a quarter.

Table 3

Ordered Probit Analysis of Recommendation Levels Net of the Consensus

Explanatory Variable	Coefficient	z-Statistic
Investment banking revenue (%)	.4167	17.35
Brokerage commission revenue (%)	.0363	3.00
Prior 6-month stock return	−.0068	−2.89
Large brokerage house dummy	−.0639	−8.60
Company size	.0038	2.89
Institutional Investor All-America Research Team dummy	.0032	.15
Wall Street Journal All-Star Analyst dummy	−.0196	−2.23
Company-specific research experience	.0012	1.42
Number of companies followed	.0070	4.64

Note. The results are from ordered probit regressions explaining individual analysts' stock recommendation levels net of the consensus (that is, median) recommendation level at the end of each quarter (March, June, September, December) for 1995–2003. Observations are excluded if the analyst issued no new or revised recommendation in the preceding 12 months. The regression includes observations pooled across analysts, stocks, and quarters. Data on recommendations are drawn from the Institutional Brokers Estimate System (I/B/E/S) U.S. Detail Recommendations History file for 1994–2003. Investment banking or brokerage commission revenue refer to the percentage of the brokerage firm's total revenues derived from investment banking or brokerage commissions. The large brokerage house dummy is an indicator variable that equals one if a brokerage house is in the top quartile of all houses, based on the number of analysts issuing stock recommendations listed in I/B/E/S in a given calendar year. Company size is the natural logarithm of the market capitalization of the company followed, measured 12 months prior to the end of the current month. The *Institutional Investor* All-America Research Team and *Wall Street Journal* All-Star Analyst dummies are indicator variables that equal one if the recommending analyst was listed as an All-America Research Team member or All-Star Analyst in the most recent analyst ranking. Company-specific research experience is the natural log of one plus the number of days that an analyst has been issuing I/B/E/S research on a company. Number of companies followed equals the natural log of one plus the number of companies followed by an analyst in the current calendar year. The regression includes dummy variables for two-digit I/B/E/S sector industry group industries and for calendar quarters. Test statistics are based on a robust variance estimator. The number of observations is 213,011; the p-value of the χ^2 test is <.0001.

take ordered values from −4 (strongly pessimistic) to 4 (strongly optimistic) in increments of .5, we estimate the regression as an ordered probit model.[18] The Z-statistics are based on a robust (Huber-White sandwich) variance estimator.

Table 3 shows the regression estimate. The coefficients of IB revenue percentage and commission revenue percentage are both positive. This finding implies that greater conflicts with IB and brokerage businesses lead an analyst to issue a higher recommendation on a stock relative to the consensus. Stocks followed by busier analysts and stocks of larger companies receive higher recommendations relative to the consensus. Stocks that experience a price run-up over the prior 6 months, stocks followed by analysts at large brokerage houses, and stocks followed by *WSJ* All-Star Analysts all receive lower recommendations relative to the consensus. All of these relations are highly statistically significant.

To provide a sense of the magnitude of the main effects of interest, we show in Table 4 the derivatives of the probability of each net recommendation level

[18] Notice that recommendation levels can take integer values from 1 to 5, and the median recommendation can take values from 1 to 5 in increments of .5. See Greene (2003) for a detailed exposition of the ordered probit model.

Table 4

Marginal Effects and Sample Distribution for the Ordered Probit Regression in Table 3

	Recommendation Level Net of the Consensus														
	−4	−3.5	−3	−2.5	−2	−1.5	−1	−.5	0	.5	1	1.5	2	2.5	3
Investment banking revenue (%)	−.00031	−.0002	−.0026	−.0010	−.0199	−.0086	−.0744	−.0321	.0123	.0325	.0671	.0077	.0188	.0002	.0003
Brokerage commission revenue (%)	−.00003	−.00001	−.0002	−.00009	−.0017	−.0008	−.0065	−.0028	.0011	.0028	.0059	.0007	.0016	.00002	.00003
Observed frequency	.0001	.0001	.0016	.0007	.0176	.0094	.1241	.0948	.4940	.0937	.1289	.0111	.0233	.0002	.0003

Note. Shown is the derivative of the probability of each net recommendation level with respect to investment banking or brokerage revenue percentage, estimated from the ordered probit regression in Table 3. Investment banking and brokerage commission revenue refer to the percentage of the brokerage firm's total revenues derived from investment banking and brokerage commissions. The last row shows observed frequency of each net recommendation level as a proportion of the sample of 213,011 observations.

with respect to IB revenue and commission revenue percentages.[19] Thus, for example, a 1-standard-deviation increase in IB revenue percentage increases the probability of an optimistic recommendation (that is, a net recommendation level greater than zero) by .1193 × (.0325 + .0671 + . . . + .0003) = .0151. Compared to the unconditional probability of an optimistic recommendation by an analyst, this represents an increase of about 5.9 percent (.0151/.2575). The effect of a change in commission revenue percentage is much smaller. A 1-standard-deviation increase in commission revenue percentage increases the probability of an optimistic recommendation by .2475 × .01105 = .0027, or about 1 percent (.0027/.2575) of the unconditional probability. Thus, despite possible concerns about a loss of reputation, analysts seem to respond to conflicts of interest, particularly those stemming from IB.

5. Conflicts and Investor Response to Recommendation Revisions

5.1 Stock Price Response

This section examines whether an analyst's credibility with investors is related to the degree of conflict faced. We interpret the reaction of stock prices to a recommendation revision as an indication of an analyst's credibility. Our analysis focuses on revisions in recommendation levels, rather than on recommendation levels per se, because revisions are discrete events that are likely to be salient for investors, and previous research finds that revisions have significant information content (see, for example, Womack 1996; Jegadeesh et al. 2004). To capture the effects of the most commonly observed and economically important types of revisions, we structure our tests around four basic categories: added to strong buy, added to buy or strong buy, dropped from strong buy, and dropped from buy or strong buy.[20] These four categories are defined to include initiations, resumptions, and discontinuations of coverage because such events also reflect analysts' positive or negative views about a company.[21] Thus, for example, we consider a stock to be added to strong buy under two scenarios: (*a*) the recommendation level is raised to strong buy from a lower level or (*b*) coverage is

[19] Notice that, for each explanatory variable, these derivatives sum to zero across all the net recommendation levels.

[20] Our analysis focuses on these four types of revisions instead of the other four (added to strong sell, and so forth) because, as shown in Table 1, sell and strong sell recommendations are quite rare. But note that dropped-from-buy and dropped-from-buy-or-strong-buy revisions can entail movement to the sell or strong sell category.

[21] We use the I/B/E/S Stopped Recommendations file to determine instances in which a brokerage firm discontinued coverage of a company. This file contains numerous cases in which an analyst stops coverage of a stock only to issue a new recommendation a month or two later. Conversations with I/B/E/S representatives indicate that such events likely represent pauses in coverage due to company quiet periods or analysts' reassignments within a brokerage house. We define a stopped coverage event to be a true stoppage only if the analyst does not issue a recommendation on the stock over the subsequent 6 months.

initiated or resumed at the level of strong buy.[22] Defining revisions in this fashion yields a sample of 94,892 recommendation revisions made over the 1994–2003 period.

5.1.1. Average Response

We compute the abnormal return on an upgraded or downgraded stock over day t as the return (including dividends) on the stock minus the return on the Center for Research in Security Prices equal-weighted market portfolio of New York Stock Exchange (NYSE), American Stock Exchange, and NASDAQ stocks. The cumulative abnormal return (CAR) on the stock over days t_1 to t_2 relative to the revision date (day 0) is measured as the sum of the abnormal returns over those days. Table 5 shows mean and median CARs for three windows: days -1 to 0, -1 to 1, and -5 to 5. The t-statistics for the difference of the mean abnormal returns from zero are computed as in Brown and Warner (1985) and are shown in parentheses. The p-values for the Wilcoxon test are reported in parentheses with the medians.

It is clear from Table 5 that recommendation revisions have large effects on stock prices. For example, when a stock is added to the strong-buy list, it experiences a mean abnormal return of about 2 percent over the 2-day revision period. Downgrades have even larger effects on stock prices than do upgrades. Strikingly, the 2-day mean abnormal return around the dropped-from-strong-buy list is -4 percent. Median values are consistently smaller in magnitude than are means, and this finding indicates that some revisions lead to price reactions of a very large magnitude. Mean and median 2-day abnormal returns are statistically different from zero for all four groups of forecast revisions. The magnitudes of abnormal returns are somewhat larger over the 3-day and 11-day windows than over the 2-day window. Overall, these returns are consistent with those found by prior research that examines the average stock price impact of recommendation revisions (for example, Womack 1996; Jegadeesh et al. 2004).

5.1.2. Cross-Sectional Analysis

Table 6 contains cross-sectional regressions of stock price reactions to recommendation revisions over days -1 to 1. The main explanatory variables of interest in these regressions are our revenue-based measures of the magnitudes of IB and brokerage conflicts. We include controls for the size of an analyst's employer, the size of the company followed, and measures of an analyst's reputation, experience, and workload.[23] We estimate a separate regression for each

[22] Note that the definitions of our four recommendation revision groups imply that stocks can be added to a group more than once on a given day. Nonetheless, excluding days on which a stock experiences multiple revisions does not change any of our qualitative results.

[23] Prior research finds that analysts who have more experience, carry lower workloads, or are employed by larger firms tend to generate more precise research (see, for example, Clement 1999; Jacob, Lys, and Neale 1999; Mikhail, Walther, and Willis 1997). In addition, more reputed analysts tend to generate timelier and more accurate research (see, for example, Stickel 1992; Hong and Kubik 2003). We expect such analysts to be more influential with investors.

Table 5

Cumulative Abnormal Returns surrounding Revisions in Analyst Stock Recommendations

Recommendation Revision	Days −1 to 0 Mean (t-Statistic)	Days −1 to 0 Median (p-Value)	Days −1 to 0 N	Days −1 to 1 Mean (t-Statistic)	Days −1 to 1 Median (p-Value)	Days −1 to 1 N	Days −5 to 5 Mean (t-Statistic)	Days −5 to 5 Median (p-Value)	Days −5 to 5 N
Upgrades:									
Added to strong buy	.0207	.0109	24,560	.0240	.0130	24,556	.0263	.0187	24,499
	(49.53)*	(.000)		(46.89)*	(.000)		(26.84)*	(.000)	
Added to buy or strong buy	.0149	.0071	36,879	.0165	.0085	36,875	.0207	.0128	36,780
	(46.47)*	(.000)		(42.01)*	(.000)		(27.53)*	(.000)	
Downgrades:									
Dropped from buy or strong buy	−.0337	−.0126	33,322	−.0358	−.0155	33,262	−.0491	−.0287	33,197
	(−56.21)*	(.000)		(−48.75)*	(.000)		(−34.92)*	(.000)	
Dropped from strong buy	−.0399	−.0153	22,825	−.0427	−.0183	22,795	−.0570	−.0326	22,767
	(−49.88)*	(.000)		(−43.58)*	(.000)		(−30.38)*	(.000)	

Note. The sample of recommendation revisions is drawn from the Institutional Brokers Estimate System (I/B/E/S) U.S. Detail Recommendations History file for 1994–2003. Recommendation revisions include recommendation changes and initiations, resumptions, and discontinuations in coverage. Day 0 is the revision date. Recommendation revisions are classified according to the level of any existing recommendation and whether coverage is being initiated or dropped. For example, a revision by an analyst is classified as added to strong buy if the new recommendation is strong buy and (*a*) the previous recommendation was lower than strong buy or (*b*) analyst coverage by the brokerage house is resumed or initiated. A recommendation is classified as dropped from strong buy if the previous recommendation was strong buy and (*a*) the new recommendation is lower than strong buy or (*b*) research coverage on the company is stopped. The t-statistics for the difference from zero are computed as in Brown and Warner (1985). The p-values for the difference from zero are from a Wilcoxon test.

* Statistically significant at the 1% level in two-tailed tests.

Table 6

Cross-Sectional Regressions of Cumulative Abnormal Returns over Days −1 to +1 surrounding Recommendation Revisions

Explanatory Variable	Added to Strong Buy	Added to Buy or Strong Buy	Dropped from Buy or Strong Buy	Dropped from Strong Buy
Intercept	.0369	.0412	−.2294	−.2224
	(7.66)**	(11.21)**	(−31.31)**	(−29.25)**
Investment banking revenue (%)	−.0262	−.0139	−.0200	−.0354
	(−5.65)**	(−3.57)**	(−2.74)**	(−3.92)**
Brokerage commission revenue (%)	−.0187	−.0148	−.0089	−.0013
	(−6.51)**	(−6.43)**	(−2.39)*	(−.29)
Large brokerage house dummy	.0116	.0088	−.0242	−.0220
	(7.46)**	(6.88)**	(−12.79)**	(−10.25)**
Company size	−.0056	−.0041	−.0004	.0018
	(−16.13)**	(−15.40)**	(−.97)	(3.77)**
Institutional Investor All-America Research Team dummy	.0159	.0122	−.0148	−.0207
	(4.11)**	(3.82)**	(−2.93)**	(−3.28)**
Wall Street Journal All-Star Analyst dummy	.0015	.0013	−.0011	.0045
	(.81)	(.84)	(−.48)	(1.78)
Company-specific research experience	.0017	.0019	.0039	.0018
	(8.42)**	(12.49)**	(7.37)**	(3.21)**
Number of companies followed	−.0012	−.0016	.0007	.0008
	(−2.97)**	(−5.37)**	(1.49)	(1.31)
Observations	19,440	28,665	28,618	19,632
Adjusted R^2	.038	.0240	.028	.035
P-Value of *F*-test	<.0001	<.0001	<.0001	<.0001

Note. Shown are coefficient estimates and (in parentheses) *t*-statistics from ordinary least squares regressions. Day 0 is the recommendation revision date. Data on recommendations are drawn from the Institutional Brokers Estimate System (I/B/E/S) U.S. Detail Recommendations History file for 1994–2003. Investment banking and brokerage commission revenue refer to the percentages of a brokerage firm's total revenues derived from investment banking and brokerage commissions. The large brokerage house dummy is an indicator variable that equals one if a brokerage house is in the top quartile of all houses, based on the number of analysts issuing stock recommendations listed in I/B/E/S in a given calendar year. Company size is the natural logarithm of the market capitalization of the company followed, measured 12 months prior to the end of the current month. The *Institutional Investor* All-America Research Team and *Wall Street Journal* All-Star Analyst dummies are indicator variables that equal one if the recommending analyst was listed as an All-America Research Team member or All-Star Analyst in the most recent analyst ranking. Company-specific research experience is the natural log of one plus the number of days that an analyst has been issuing I/B/E/S research on a company. Number of companies followed equals the natural log of one plus the number of companies followed by an analyst in the current calendar year. All regressions include dummy variables for calendar-year and two-digit I/B/E/S sector industry group industries (not reported). The *t*-statistics are based on a robust variance estimator.

* Statistically significant at the 5% level in two-tailed tests.

** Statistically significant at the 1% level in two-tailed tests.

of the four groups of recommendation revisions. The t-statistics based on a robust variance estimator are reported in parentheses.

The coefficient on IB revenue percentage is statistically significantly negative for both upgrades and downgrades. The coefficient on brokerage commission revenue percentage is also negative in all four regressions; it is statistically significant in all cases, except for the dropped-from-strong-buy revisions.[24] Collectively, these results favor the rational discounting hypothesis over the naive investor hypothesis. The magnitudes of these effects are nontrivial. For instance, a 1-standard-deviation increase in IB revenue percentage leads to a change of about $-.31$ ($-.42$) percentage points in the 3-day abnormal return around the move to (from) a strong buy recommendation. Similarly, a 1-standard-deviation increase in brokerage commission revenue percentage leads to a change of about $-.37$ ($-.22$) percentage points in the corresponding abnormal return around the move to (from) a buy or strong buy recommendation.[25]

The results for control variables are also noteworthy. The dummy variable for a large analyst employer is positively (negatively) related to the market reaction to upgrades (downgrades). This finding is consistent with the idea that revisions by analysts employed at larger brokerage houses (which tend to be more reputable) have more credibility with investors. The size of the company followed is negatively (positively) related to the market reaction to upgrades (downgrades), which is consistent with the notion that, for larger companies, an analyst's recommendation competes with more alternative sources of information and advice.

Revisions by *II* All-America Research Team analysts are positively (negatively) related to the stock price reaction to upgrades (downgrades), which suggests that they wield more influence with investors. This is a notable finding; we are unaware of previous work documenting a relation between an analyst's reputation and the stock price reaction to both upgrades and downgrades. As the coefficient on the *WSJ* All-Star Analyst dummy indicates, however, being designated as a *WSJ* All-Star Analyst does not seem to enhance the credibility of an analyst's recommendations.[26] The absence of an effect here is somewhat

[24] These and all subsequent regression results in this article are qualitatively similar when we winsorize the dependent variable at the first and ninety-ninth percentiles of its distribution.

[25] For each group of revisions (such as added to strong buy), we also estimate the regression after excluding similar revision events that a stock experiences within 3 days of a given revision event. These results are qualitatively similar to those reported in Tables 6 and 8. We also examine the possibility that investors perceived the conflicts to be more severe, and hence discounted them more, in securities firms that were charged by regulators (that is, the 10 firms that were part of the global analyst settlement) than in other firms. We do this by interacting both investment banking (IB) revenue percentage and brokerage commission revenue percentage variables in the regression with binary (0, 1) dummy variables for securities firms that are part of the global analyst settlement and firms that are not. We find no significant differences between the two groups of firms in their coefficients on IB revenue percentage and commission revenue percentage.

[26] Although *II* All-America Research Team and *WSJ* All-Star Analyst dummies both measure aspects of an analyst's reputation, they are not highly correlated. The correlation coefficient is .14 across all upgrades and .13 across all downgrades.

surprising given that the *WSJ* has a much broader readership base than that of *II*. One explanation is that *II* analyst rankings are based on an opinion poll of money managers, who control substantial assets and therefore directly affect stock prices, while *WSJ* rankings are based on strictly quantitative measures of analysts' past stock-picking or forecasting performance.

The market reaction to upgrades is positively related to an analyst's company-specific research experience. This finding suggests that more experienced analysts tend to be more influential with investors. But the reaction to downgrades is also positively related to analysts' experience. Finally, the stock price reaction to upgrades is negatively related to analysts' workload. This finding suggests that busier analysts' opinions tend to get discounted by the market. All of these relations are statistically significant.

5.2. *Response of Trading Volume*

In this section, we measure analysts' credibility via changes in the volume of trade around recommendation revisions.[27] Revisions of analysts' recommendations can affect trading volumes by inducing investors to rebalance their portfolios to reflect updated beliefs.

5:2.1. Average Response

We compute the abnormal volume for a trading day t as the mean-adjusted share turnover for stock i:[28]

$$e_{it} = v_{it} - v_i, \tag{1}$$

where v_{it} is the trading volume of stock i over day t divided by common shares outstanding on day t and v_i is the mean of v_{it} over days -35 to -6.

The cumulative abnormal volume (CAV) for stock i over days t_1 to t_2 is measured in the following way:

$$\mathrm{CAV}^i t_1, t_2 = \sum_{t=t_1}^{t_2} e_{it}. \tag{2}$$

Table 7 shows mean and median CAV values over three windows surrounding revisions in analyst stock recommendations. Over the 2-day revision period, the mean abnormal volume is positive for both upgrades and downgrades, but its magnitude is substantially larger for downgrades. The move to (from) the strong-buy list increases a stock's trading volume by a mean of about .9 percent (2.6 percent) of the outstanding shares, compared to a normal day's volume. For longer windows, the mean abnormal volumes are substantially higher for down-

[27] Many prior studies have used trading volume to examine investors' response to informational events (see, for example, Shleifer 1986; Jain 1988; Jarrell and Poulsen 1989; Meulbroek 1992; Sanders and Zdanowicz 1992).

[28] This approach has been used in a number of prior studies (for example, Shleifer 1986; Vijh 1994; Michaely and Vila 1996).

Table 7

Cumulative Abnormal Trading Volumes surrounding Announcements of Revisions in Stock Recommendations by Analysts

Recommendation revision	Days −1 to 0			Days −1 to 1			Days −5 to 5		
	Mean (*t*-Statistic)	Median (*p*-Value)	*N*	Mean (*t*-Statistic)	Median (*p*-Value)	*N*	Mean (*t*-Statistic)	Median (*p*-Value)	*N*
Upgrades:									
Added to strong buy	.0086	.0011		.0097	.0015		.0071	.0030	
	(8.89)*	(.000)	24,506	(8.18)*	(.000)	24,502	(3.13)*	(.000)	24,488
Added to buy or strong buy	.0053	.0002		.0058	.0004		.0020	.0008	
	(5.08)*	(.000)	36,800	(4.54)*	(.000)	36,796	(.818)	(.000)	36,766
Downgrades:									
Dropped from buy or strong buy	.0217	.0010		.0265	.0014		.0381	.0039	
	(114.47)*	(.000)	33,291	(114.14)*	(.000)	33,232	(85.70)*	(.000)	33,175
Dropped from strong buy	.0259	.0017		.0315	.0025		.0453	.0057	
	(128.76)*	(.000)	22,808	(127.86)*	(.000)	22,779	(96.03)*	(.000)	22,756

Note. The abnormal volume for stock *i* on day *t* is computed from daily Center for Research in Security Prices data as $e_{it} = v_{it} - v_i$, where v_{it} is the volume on day *t* and v_i is the average volume over days −35 to −6 relative to the recommendation revision date (day 0). All share volumes are normalized by dividing by common shares outstanding on the same day. The *p*-values are from a Wilcoxon test.

*Statistically significant at the 1% level in two-tailed tests.

grades. The median values are lower than the mean values. Each mean and median abnormal volume is statistically greater than zero, with a p-value below .01. Clearly, revisions of stock recommendations by analysts generate trading.

5.2.2. Cross-Sectional Analysis

Table 8 presents cross-sectional regressions explaining CAVs over days -1 to 1 surrounding the recommendation revisions. The explanatory variables in the regressions are the same as in regressions of CARs in Section 5.1.2. The results provide strong support for the rational discounting hypothesis. The coefficients on both the IB revenue percentage and commission revenue percentage variables are generally statistically significant and negative (positive) for both groups of upgrades (downgrades). The magnitudes of these effects are nontrivial. For example, a 1-standard-deviation increase in IB revenue percentage leads to a change in the 3-day abnormal volume around the addition (omission) of a stock to (from) the strong-buy list of about $-.12$ percent (.36 percent) of the outstanding shares; a corresponding change in the commission revenue percentage results in a change in the abnormal volume of about $-.15$ percent (.22 percent).

Recommendation revisions by larger brokerage houses generate more trading. The abnormal volume is also larger for revisions involving smaller companies. Revisions by *II* All-America Research Team members generate statistically significantly more abnormal volume for the dropped from buy or strong-buy group. Upgrades (downgrades) by more experienced analysts result in larger (smaller) abnormal volumes, and upgrades by busier analysts are less credible.

6. Conflicts and the Performance of Recommendation Revisions

We next consider the investment performance of analysts' recommendation revisions over periods of up to 12 months. Here, the choice of the benchmark used to compute abnormal returns is somewhat more important than it is in Section 5.1, where we measure abnormal returns over a few days around the revision. But the results here are likely to be less sensitive to the benchmark employed than are those in studies of long-run stock performance, where the time period of interest can be as long as 5–10 years (see, for example, Agrawal, Jaffe, and Mandelker 1992; Agrawal and Jaffe 2003).

6.1. Average Performance

We use an approach similar to Barber, Lehavy, and Trueman (2007). To evaluate the performance of stocks over a given window, say, months 1–12 following the month of their inclusion (month 0) in a given group of revisions such as the added-to-strong-buy list, we form a portfolio p that initially invests \$1 in each recommendation. Each recommended stock remains in the portfolio until month 12 or the month that the stock is either downgraded or dropped from coverage by the securities firm, whichever is earlier. If multiple securities firms recommend a stock in a given month, the stock appears multiple times in the

Table 8

Cross-Sectional Regressions of Cumulative Abnormal Trading Volumes over Days −1 to +1 surrounding Recommendation Revisions

Explanatory Variable	Added to Strong Buy	Added to Buy or Strong Buy	Dropped from Buy or Strong Buy	Dropped from Strong Buy
Intercept	.0083	.0042	.0946	.0828
	(2.65)**	(1.90)	(13.72)**	(15.01)**
Investment banking revenue (%)	−.0100	−.0085	.0140	.0304
	(−3.31)**	(−2.26)*	(2.18)*	(3.63)**
Brokerage commission revenue (%)	−.0057	−.0059	.0087	.0055
	(−1.76)	(−4.13)**	(2.76)**	(1.45)
Large brokerage house dummy	.0058	.0038	.0168	.0171
	(3.72)**	(4.50)**	(11.12)**	(9.48)**
Company size	−.0031	−.0018	−.0023	−.0041
	(−9.54)**	(−12.30)**	(−7.60)**	(−11.40)**
Institutional Investor All-America Research Team dummy	.0035	.0033	.0084	.0046
	(1.74)	(1.88)	(2.32)*	(1.21)
Wall Street Journal All-Star Analyst dummy	.0008	.0013	.0023	−.0006
	(.74)	(1.42)	(1.36)	(−.29)
Company-specific research experience	.0010	.0010	−.0041	−.0019
	(8.39)**	(11.19)**	(−6.18)**	(−4.11)**
Number of companies followed	−.0009	−.0013	−.0001	−.0005
	(−3.49)**	(−6.23)**	(−.38)	(−.99)
Observations	19,431	28,653	28,594	19,619
Adjusted R^2	.025	.019	.030	.042
p-Value of F-test	<.0001	<.0001	<.0001	<.0001

Note. Shown are coefficient estimates and (in parentheses) t-statistics from ordinary least squares regressions. Day 0 is the recommendation revision date. Data on recommendations are drawn from the Institutional Brokers Estimate System (I/B/E/S) U.S. Detail Recommendations History file for 1994–2003. Investment banking and brokerage commission revenue refer to the percentage of brokerage firm's total revenues derived from investment banking and brokerage commissions. The large brokerage house dummy is an indicator variable that equals one if a brokerage house is in the top quartile of all houses, based on the number of analysts issuing stock recommendations listed in I/B/E/S in a given calendar year. Company size is the natural logarithm of the market capitalization of the company followed, measured 12 months prior to the end of the current month. The *Institutional Investor* All-America Research Team and *Wall Street Journal* All-Star Analyst dummies are indicator variables that equal one if the recommending analyst was listed as an All-America Research Team member or All-Star Analyst in the most recent analyst ranking. Company-specific research experience is the natural log of one plus the number of days that an analyst has been issuing I/B/E/S research on a company. Number of companies followed equals the natural log of one plus the number of companies followed by an analyst in the current calendar year. All regressions include dummy variables for calendar-year and two-digit I/B/E/S sector industry group industries (not reported). The t-statistics are based on a robust variance estimator.

* Statistically significant at the 5% level in two-tailed tests.

** Statistically significant at the 1% level in two-tailed tests.

portfolio that month, once for each securities firm with a strong buy recommendation. The portfolio return for calendar month t is given by

$$R_{pt} = \sum_{i=1}^{n_t} x_{it} \times R_{it} \bigg/ \sum_{i=1}^{n_t} x_{it}, \tag{3}$$

where R_{it} is the month t return on recommendation i, x_{it} is one plus the compound return on the recommendation from month 1 to month $t-1$ (that is, x_{it} equals one for a stock that was recommended in month t), and n_t is the number of recommendations in the portfolio. This calculation yields a time series of monthly returns for portfolio p.

We compute the abnormal performance of portfolio p as the estimate of the intercept term α_p from the Fama and French (1993) three-factor model. Accordingly, we estimate the following time-series regression for portfolio p:

$$R_{pt} - R_{ft} = \alpha_p + \beta_{1p}(R_{mt} - R_{ft}) + \beta_{2p}\mathrm{SMB}_t + \beta_{3p}\mathrm{HML}_t + \varepsilon_{pt}, \quad t = \text{January 1994 to December 2003}, \tag{4}$$

where R_f is the risk-free rate, R_m is the return on the value-weighted market index, SMB equals the monthly return on a portfolio of small firms minus the return on a portfolio of big firms, and HML is the monthly return on a portfolio of firms with high book-to-market ratio minus the return on a portfolio of firms with low book-to-market ratio. The error term in the regression is denoted ε. The time series of monthly returns on $R_m - R_f$, SMB, and HML are obtained from Kenneth French's Web site.[29] We repeat this procedure for each time window of interest, such as months 1–3, and for each group of revisions, such as the dropped-from-strong-buy list.

Table 9 shows the performance of analysts' recommendation revisions. Over the period of 3 months following the month of recommendation revision, the average abnormal returns for upgrades are positive, and the returns for downgrades are negative. The magnitudes of these returns are nontrivial. For example, the addition of a stock to the strong-buy list has an abnormal monthly return of about .875 percent, or about 2.62 percent over the 3-month period. The pattern is generally similar over longer windows. For example, over months 1–12, the abnormal monthly return for the added-to-strong-buy list is .679 percent, or about 8.15 percent over the 12-month period. The abnormal returns are significantly different from zero for upgrades in all cases; they are statistically insignificant for downgrades in all cases except one.

[29] Kenneth R. French, Fama/French Factors (file F-F_Research_Data_Factors.zip at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html).

Table 9
Medium-Term Investment Performance of Recommendation Revisions

	Months 1–3		Months 1–6		Months 1–12	
Portfolio	Abnormal Monthly Return (%)	*t*-Statistic	Abnormal Monthly Return (%)	*t*-Statistic	Abnormal Monthly Return (%)	*t*-Statistic
Added to strong buy	.875	6.12**	.758	6.12**	.679	5.70**
Added to buy or strong buy	.586	4.49**	.511	4.82**	.503	5.38**
Dropped from buy or strong buy	−.361	−1.60	−.260	−1.28	−.072	−.44
Dropped from strong buy	−.367	−1.58	−.395	−2.00*	−.231	−1.49

Note. Abnormal returns are reported for three event windows relative to the month of revision (month 0) and are computed using an approach similar to that in Barber, Lehavy, and Trueman (2007). The abnormal return is the estimated intercept from a time-series regression of 114 monthly portfolio returns using the Fama and French (1993) three-factor model.
* Statistically significant at the 5% level in two-tailed tests.
** Statistically significant at the 1% level in two-tailed tests.

6.2. *Cross-Sectional Analysis*

Table 10 shows the results of a regression similar to that in Section 5.1.2, except that the dependent variable here is the average monthly abnormal return for a firm over months 1–12 following the month of a recommendation revision. We compute this abnormal return by estimating a time-series regression similar to that in equation (4) over months 1–12 for each stock in a sample of recommendation revisions. The intercept from this regression is our estimate of the performance of the recommendation revision. Observations involving recommendation revisions on a stock that occur within 12 months of an earlier revision are omitted from each regression.[30]

In each regression result reported in Table 10, the coefficients of IB revenue percentage and commission revenue percentage are not statistically significantly different from zero. These results favor the rational discounting hypothesis, at least for the marginal investor. The performance of both groups of recommendation upgrades is negatively related to company size; the performance of one group of downgrades is positively related to the dummy variable for *WSJ* All-Star Analysts. None of the other variables is statistically significant.

7. Bubble versus Postbubble Periods

We next exploit the fact that our sample spans both the late-1990s U.S. stock bubble and a postbubble period. During the bubble period, initial public offerings, merger activities, and stock prices were near record highs, and media attention was focused on analysts' pronouncements. We therefore examine whether analysts' behavior and investors' responses to analysts' recommendations differed during the bubble and postbubble periods. Given the euphoria on Wall

[30] The results are qualitatively similar when we include these observations.

Table 10

Cross-Sectional Regressions of Average Monthly Abnormal Returns following Recommendation Revisions over Months 1–12

Explanatory Variable	Added to Strong Buy	Added to Buy or Strong Buy	Dropped from Buy or Strong Buy	Dropped from Strong Buy
Intercept	.0523	.0089	−.0646	−.0821
	(1.81)	(.49)	(−6.81)**	(−6.55)**
Investment banking revenue (%)	−.0089	−.0018	.0042	−.0068
	(−1.23)	(−.29)	(.64)	(−.87)
Brokerage commission revenue (%)	.0064	.0059	.0057	.0031
	(1.32)	(1.54)	(1.21)	(.75)
Large brokerage house dummy	.0009	−.0027	.0016	.0015
	(.38)	(−1.32)	(.72)	(.77)
Company size	−.0013	−.0017	−.0007	−.0007
	(−2.74)**	(−4.18)**	(−1.71)	(−1.54)
Institutional Investor All-America analyst dummy	−.0029	.0001	−.0016	−.0009
	(−.58)	(.01)	(−.44)	(−.23)
Wall Street Journal All-Star Analyst dummy	.0031	.0002	−.0029	.0056
	(1.24)	(.12)	(−1.42)	(2.29)*
Company-specific research experience	.0004	.0004	.0004	.0004
	(1.08)	(1.80)	(.76)	(.92)
Number of companies followed	−.0011	−.0008	−.0002	−.0002
	(−1.61)	(−1.79)	(−.45)	(−.47)
Observations	6,411	8,851	10,644	8,368
Adjusted R^2	.026	.023	.019	.020
p-Value of F-test	<.0001	<.0001	<.0001	<.0001

Note. Shown are the coefficient estimates and (in parentheses) t-statistics from ordinary least squares regressions. Month 0 is the month of recommendation revision. The abnormal return is the estimated intercept from a time-series regression of monthly portfolio returns in accordance with the Fama and French (1993) three-factor model. Data on recommendations are drawn from the Institutional Brokers Estimate System (I/B/E/S) U.S. Detail Recommendations History file for 1994–2003. Investment banking and brokerage commission revenue data refer to the percentage of the brokerage firm's total revenues derived from investment banking and brokerage commissions. The large brokerage house dummy is an indicator variable that equals one if a brokerage house is in the top quartile of all houses, based on the number of analysts issuing stock recommendations on I/B/E/S in a given calendar year. Company size is the natural logarithm of the market capitalization of the company followed, measured 12 months prior to the end of the current month. The *Institutional Investor* All-America Research Team and *Wall Street Journal* All-Star Analyst dummies are indicator variables that equal one if the recommending analyst was listed as an All-America Research Team member or All-Star Analyst in the most recent analyst ranking. Company-specific research experience is the natural log of one plus the number of days that an analyst has been issuing I/B/E/S research on a company. Number of companies followed equals the natural log of one plus the number of companies followed by an analyst in the current calendar year. All regressions include dummy variables for calendar-year and two-digit I/B/E/S sector industry group industries (not reported). The t-statistics are based on a robust variance estimator.

* Statistically significant at the 5% level in two-tailed tests.

** Statistically significant at the 1% level in two-tailed tests.

Table 11
Ordered Probit Regression of Recommendation Levels Net of the Consensus for Bubble versus Postbubble Periods

	Bubble	Postbubble	p-Value
Investment banking revenue (%)	.5103*	.3089*	<.001
Brokerage revenue (%)	−.1868*	.2286*	<.001

Note. The explanatory variables are as in Table 3, except that (a) the investment banking revenue and brokerage commission revenue percentage variables are interacted with dummy variables for the bubble or postbubble period and (b) calendar-quarter dummies are replaced with a postregulation indicator (which is equal to one for quarters after May 2002). Shown are the coefficient estimates of investment banking and brokerage revenue percentage variables for the bubble and postbubble periods and the p-value for the difference in the coefficient estimate between the two periods. All test statistics use robust variance estimators.
* Statistically significant at the 1% level in two-tailed tests.

Street and among investors during the bubble, analysts appear to have been under acute pressure to generate IB fees and brokerage commissions. As for the response of investors, the rational discounting hypothesis predicts greater discounting of analysts' opinions during this period in response to heightened conflicts, while the naive investor hypothesis predicts less discounting.

We estimate regressions similar to those for relative recommendation levels (Table 3), those for announcement abnormal returns (Table 6), those for announcement abnormal volumes (Table 8), and those for 12-month investment performance of recommendation revisions (Table 10), except that we now interact IB revenue percentage and commission revenue percentage with dummy variables for the bubble (January 1996–March 2000) and postbubble (April 2000–December 2003) periods. Accordingly, we restrict the sample period for these regressions to January 1996–December 2003. For regressions corresponding to those with results shown in Table 3, we also replace the calendar-quarter dummies with a postregulation indicator (equal to one for quarters ending after May 2002). In May 2002, both the NYSE and the National Association of Securities Dealers considerably tightened the regulations on the production and dissemination of sell-side analyst research.[31] The findings of Barber et al. (2006) and Kadan et al. (forthcoming) suggest that these regulations exerted a downward pressure on recommendation levels. The regression results are presented in Tables 11 and 12. To save space, we report only the coefficient estimates for IB revenue percentage and commission revenue percentage.

The results in Table 11 show that analysts appear to have inflated their recommendations in response to IB conflicts during both the bubble and postbubble periods. But the magnitude of this effect is substantially greater during the bubble period than during the postbubble period. This difference is statistically significant. The magnitude of the effect is smaller for brokerage conflicts than for IB conflicts during both periods. In fact, the effect for brokerage conflicts is negative

[31] See NYSE Amended Rule 472, "Communications with the Public," and National Association of Securities Dealers Rule 2711, "Research Analysts and Research Reports."

Table 12

Ordinary Least Squares Regressions of Abnormal Returns, Abnormal Volumes, and Abnormal Stock Performance for Bubble and Postbubble Periods

	Added to Strong Buy			Added to Buy or Strong Buy			Dropped from Buy or Strong Buy			Dropped from Strong Buy		
	Bubble	Postbubble	p-Value	Bubble	Postbubble	p-Value	Bubble	Postbubble	p-Value	Bubble	Postbubble	p-Value
CARs, days −1 to 1:												
Investment banking revenue (%)	−.0248**	−.0120	.083	−.0121**	−.0080	.517	−.0125	−.0379**	.027	−.0361**	−.0345**	.908
Brokerage revenue (%)	−.0114**	−.0105**	.827	−.0099**	−.0110**	.720	−.0063	−.0208**	.003	.0017	−.0114*	.024
CAVs, days −1 to 1:												
Investment banking revenue (%)	−.0076	−.0052	.655	−.0065	−.0082*	.699	.0257**	.0130	.214	.0555**	.0153	.002
Brokerage revenue (%)	−.0042	−.0008	.376	−.0054**	−.0031	.179	.0106*	.0139**	.521	.0046	.0141**	.056
Average monthly CARs, months 1–12:												
Investment banking revenue (%)	−.0016	−.0151	.273	.00001	.0083	.420	−.0085	.0223**	.003	−.0123	−.0051	.564
Brokerage revenue (%)	.0069	.0108	.511	.0086	.0096	.842	.0035	.0136	.101	−.0036	.0091	.019

Note. The explanatory variables are as in Tables 6, 8, and 10, except that the investment banking revenue and brokerage commission revenue percentage variables are interacted with dummy variables for the bubble or postbubble period. Shown are the coefficient estimates of the investment banking and brokerage revenue percentage variables for the bubble and postbubble periods and the p-value for the difference in the coefficient estimate between the two periods. Day (month) 0 is the recommendation revision date. All test statistics use robust variance estimators. CAR = cumulative abnormal return; CAV = cumulative abnormal volume.

* Statistically significant at the 5% level in two-tailed tests.

** Statistically significant at the 1% level in two-tailed tests.

during the bubble; it is positive and statistically significantly higher during the postbubble period.

Table 12 shows that, in regressions of 3-day abnormal returns, the coefficients of both IB revenue percentage and commission revenue percentage are negative and statistically significant during the bubble period for both groups of upgrades. For the added-to-strong-buy group, the coefficient of IB revenue percentage is significantly lower during the bubble period than during the postbubble period. For downgrades, the coefficients of both variables are generally negative in both periods, and they are statistically significantly lower during the postbubble period.

In regressions of 3-day abnormal volumes, the coefficients of IB revenue percentage and commission revenue percentage are negative for upgrades and positive for downgrades in all cases, both during and after the bubble. These coefficients are not statistically significantly different between the bubble and postbubble periods for both groups of upgrades and one group of downgrades. For the dropped-from-strong-buy group, the coefficient of IB revenue percentage is statistically significantly larger during the bubble period than during the postbubble period, but the coefficient of the commission revenue percentage is statistically significantly smaller. In regressions of 12-month postrecommendation stock performance, the coefficients of both variables are statistically insignificant both during and after the bubble period in nearly all cases, and this finding is consistent with the results shown in Table 10 for the full sample period.

Overall, analysts appear to respond to IB conflicts both during and after the bubble, but the magnitude of their response declines during the postbubble period. Perversely, while analysts do not seem to respond to brokerage conflicts during the bubble, they appear to do so after the bubble. Perhaps the intense regulatory and media focus on IB conflicts has led analysts to look for alternative avenues. Did investors discount conflicted analysts' opinions more during the bubble than in the postbubble period? The answer to this question is unclear. However, our evidence does not support the notion that investors threw caution to the wind during the bubble.

8. Summary and Conclusions

Following the collapse of the late-1990s U.S. stock market bubble, there has been a widespread hue and cry from investors and regulators over the conflicts of interest faced by Wall Street stock analysts. The discovery of e-mail messages, in which analysts were privately disparaging stocks that they were touting publicly, led to the landmark $1.4 billion settlement between a number of leading Wall Street firms and securities regulators in April 2003. The settlement requires the firms to disclose IB conflicts in analyst reports and imposes a variety of restrictions designed to strengthen the firewalls that separate research from IB. Part of the settlement funds are set aside for investor education and for research produced by independent firms. The settlement basically presumes that analysts respond to the conflicts by inflating their stock recommendations and that investors take analysts' recommendations at face value.

Consistent with the view of the media and regulators, we find that optimism in stock recommendations is positively related to the importance of both IB and brokerage businesses to an analyst's employer. This pattern is more pronounced during the late-1990s stock market bubble with respect to IB conflicts. However, we provide several pieces of empirical evidence that suggest that investors are sophisticated enough to adjust for this bias. First, the short-term reactions of both stock prices and trading volumes to recommendation upgrades vary negatively with the magnitude of potential IB or brokerage conflicts faced by analysts. For instance, over the 3 days surrounding an upgrade to strong buy, a 1-standard-deviation increase in the proportion of revenue from IB is associated with a .31 percentage point decrease in abnormal returns and a .12 percentage point decrease in abnormal volume. These results suggest that investors ascribe lower credibility to an analyst's upgrade when the analyst is subject to greater pressures to issue an optimistic view. For downgrades, conflict severity varies negatively with the short-term stock price reaction and positively with the short-term trading volume impact. This pattern is consistent with the idea that investors perceive an analyst to be more credible if he or she is willing to voice an unfavorable opinion on a stock despite greater pressures to be optimistic.

Second, we find no evidence that the 1-year investment performance of recommendation revisions is related to the magnitude of analysts' conflicts, either for upgrades or for downgrades. This finding suggests that, on average, investors properly discount an analyst's opinions for potential conflicts at the time the opinion is issued. Finally, investors discounted conflicted analysts' opinions during the late-1990s stock bubble, even in the face of the prevailing market euphoria. This evidence does not support the popular view that recommendations of sell-side analysts led investors to throw caution to the wind during the bubble period.

Overall, our empirical findings suggest that while analysts do respond to IB and brokerage conflicts by inflating their stock recommendations, the market discounts these recommendations after taking analysts' conflicts into account. These findings are reminiscent of the story of the nail soup told by Brealey and Myers (1991), except that here analysts (rather than accountants) are the ones who put the nail in the soup and investors (rather than analysts) are the ones to take it out. Our finding that the market is not fooled by biases stemming from conflicts of interest echoes similar findings in the literature on conflicts of interest in universal banking (for example, Kroszner and Rajan 1994, 1997; Gompers and Lerner 1999) and on bias in the financial media (for example, Bhattacharya et al., forthcoming; Reuter and Zitzewitz 2006). Finally, while we cannot rule out the possibility that some investors may have been naive, our findings do not support the notion that the marginal investor was systematically misled over the last decade by analysts' recommendations.

Appendix

This Appendix describes the characteristics of disclosing and nondisclosing private securities firms, sheds some light on their decisions to publicly disclose their income statements, and examines whether the resulting selection bias affects our main results in Table 3. Table A1 provides summary statistics of recommendation levels and characteristics of disclosing and nondisclosing private securities firms. Compared with nondisclosing firms, disclosing firms tend to be smaller and more liquid and issue somewhat more optimistic stock recommendations. The mean recommendation level is slightly higher for disclosing firms than for nondisclosing firms. The median disclosing firm is smaller and holds more liquid assets than the median nondisclosing firm. All these differences are statistically significant. The two groups of firms have similar financial leverage ratios and 2-year growth rates in total assets.

We next examine cross-sectional determinants of a private securities firm's decision to disclose its income statement. In an excellent review of the corporate disclosure literature, Healy and Palepu (2001) point out that a firm is more willing to voluntarily disclose financial information when it needs to raise external financing and when it is less concerned that the disclosure would damage its competitive position in product markets. Ceteris paribus, firms with greater growth opportunities, higher financial leverage, and less liquid resources are more likely to need external financing. They are more likely to be open with potential investors by disclosing financial information, including their income statements. Similarly, smaller firms are likely to have greater need for external financing as they try to grow. In addition, given the intense competition in the securities business, smaller private firms are also likely to be more willing to disclose their profits and profitability because they have less business at stake. For both reasons, smaller firms are likely to be more willing to disclose financial information. We control for firm size by the natural logarithm of one plus total assets in millions of dollars, for growth opportunities by the 2-year growth rate of total assets, for financial leverage by the ratio of long-term debt to total assets, and for liquidity by the ratio of cash and equivalents to total assets. We estimate a probit regression of DISCLOSER, which equals one for a disclosing firm and is zero otherwise.

In accordance with the predictions of corporate disclosure theory, the coefficients on firm size and liquidity are negative, and the coefficient on growth is positive. Contrary to the prediction, however, the coefficient on leverage is negative. All of these coefficients are highly statistically significant. The pseudo-R^2-value of this model is .08. To save space, these results are not shown in a table.

Finally, we examine whether the selection bias caused by a private securities firm's disclosure choice (and, consequently, the availability of data on IB revenue percentage and commission revenue percentage) affects our main results in Table 3. While there is no Heckman selectivity correction for the ordered probit model, there is one for the regular probit model. So we define a binary variable to

Table A1

Summary Statistics for Disclosing and Nondisclosing Private Securities Firms

Variable	Mean			Median			Sample Size	
	Disclosers	Nondisclosers	P-Value of t-Test	Disclosers	Nondisclosers	p-Value of Rank Sum Test	Disclosers	Nondisclosers
Recommendation level:								
Level	3.902	3.810	<.001	4	4	<.001	62,417	181,068
Level minus median level	.036	.010	<.001	0	0	<.001	62,417	181,068
Firm size:								
Total assets ($ millions)	383.37	1,863.52	<.001	4.05	28.43	<.001	365	615
Book equity ($ millions)	26.40	68.98	<.001	1.97	10.56	<.001	365	615
Financial leverage:								
Long-term debt to total assets	.0539	.0653	.253	0	.002	.004	365	615
Total debt to total assets	.0685	.1823	.295	0	.018	<.001	365	615
Liquidity: cash and equivalents to total assets	.2392	.1816	.001	.101	.052	.0001	365	615
2-Year growth rate	.0849	.0697	.440	.052	.020	.099	246	541

Note. Disclosers are brokers that publicly disclose their income statements, while nondisclosers are brokers that do not disclose them. The statistics for recommendation level are computed from individual analysts' recommendation levels at the end of each quarter in the sample. The median recommendation level is computed at the end of each quarter and is based on all analysts recommending a stock. The statistics for broker characteristics are computed across broker years. The firm size statistics are inflation adjusted (with Consumer Price Index numbers and with 2003 as the base year). The 2-year growth rate is $(\text{Total assets}_t / \text{Total assets}_{t-2})^{1/2} - 1$.

measure an optimistic recommendation that equals one if an analyst's recommendation level on a stock exceeds the consensus level and equals zero otherwise. We then replace the dependent variable in the regression in Section 4 with this optimistic recommendation dummy. Using the subsample of private securities firms, we estimate the resulting equation in two ways: (*a*) with a regular probit model and (*b*) with a Heckman selectivity-corrected probit model, where we use the equation described in the second paragraph of this Appendix as the selection equation. When we use approach *b*, the coefficient of the selection term (that is, the inverse Mills ratio) is statistically significant in the second-stage probit regression. What is more important for our purposes is that the sign, magnitude, and statistical significance of our main explanatory variables, the IB revenue percentage and the commission revenue percentage, are similar in the regular probit and the Heckman-corrected probit regressions. These results do not support the idea that our main findings are driven by the selection bias caused by a private securities firm's decision to disclose its revenue breakdown. To save space, these results are not shown in a table.

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Chapter 5

The Equity Risk Premium

The expected equity risk premium can be defined as the additional return an investor expects to receive to compensate for the additional risk associated with investing in equities as opposed to investing in riskless assets. It is an essential component in several cost of equity estimation models, including the buildup method, the capital asset pricing model (CAPM), and the Fama-French three factor model. It is important to note that the expected equity risk premium, as it is used in discount rates and cost of capital analysis, is a forward-looking concept. That is, the equity risk premium that is used in the discount rate should be reflective of what investors think the risk premium will be going forward.

Unfortunately, the expected equity risk premium is unobservable in the market and therefore must be estimated. Typically, this estimation is arrived at through the use of historical data. The historical equity risk premium can be calculated by subtracting the long-term average of the income return on the riskless asset (Treasuries) from the long-term average stock market return (measured over the same period as that of the riskless asset). In using a historical measure of the equity risk premium, one assumes that what has happened in the past is representative of what might be expected in the future. In other words, the assumption one makes when using historical data to measure the expected equity risk premium is that the relationship between the returns of the risky asset (equities) and the riskless asset (Treasuries) is stable. The stability of this relationship will be examined later in this chapter.

Since the expected equity risk premium must be estimated, there is much controversy regarding how the estimation should be conducted. A variety of different approaches to calculating the equity risk premium have been utilized over the years. Such studies can be categorized into four groups based on the approaches they have taken. The first group of studies tries to derive the equity risk premium from historical returns between stocks and bonds as was mentioned above. The second group, embracing a supply side model, uses fundamental information such as earnings, dividends, or overall economic productivity to measure the expected equity risk premium. A third group adopts demand side models that derive the expected returns of equities through the payoff demanded by investors for bearing the risk of equity investments.[1] The opinions of financial professionals through broad surveys are relied upon by the fourth and final group.

The range of equity risk premium estimates used in practice is surprisingly large. Using a low equity risk premium estimate as opposed to a high estimate can have a significant impact on the estimated value of a stream of cash flows. This chapter addresses many of the controversies surrounding estimation of the equity risk premium and focuses primarily on the historical calculation but also discusses the supply side model.

Calculating the Historical Equity Risk Premium

In measuring the historical equity risk premium one must make a number of decisions that can impact the resulting figure; some decisions have a greater impact than others. These decisions include selecting the stock market benchmark, the risk-free asset, either an arithmetic or a geometric average, and the time period for measurement. Each of these factors has an impact on the resulting equity risk premium estimate.

The Stock Market Benchmark

The stock market benchmark chosen should be a broad index that reflects the behavior of the market as a whole. Two examples of commonly used indexes are the S&P 500® and the New York Stock Exchange Composite Index. Although the Dow Jones Industrial Average is a popular index, it would be inappropriate for calculating the equity risk premium because it is too narrow.

We use the total return of our large company stock index (currently represented by the S&P 500) as our market benchmark when calculating the equity risk premium. The S&P 500 was selected as the appropriate market benchmark because it is representative of a large sample of companies across a large number of industries. As of December 31, 1993, 88 separate industry groups were included in the index, and the industry composition of the index has not changed since. The S&P 500 is also one of the most widely accepted market benchmarks. In short, the S&P 500 is a good measure of the equity market as a whole. Table 5-1 illustrates the equity risk premium calculation using several different market indices and the income return on three government bonds of different horizons.

Table 5-1: Equity Risk Premium with Different Market Indices

	Equity Risk Premia		
	Long-Horizon (%)	Intermediate-Horizon (%)	Short-Horizon (%)
S&P 500	6.72	7.22	8.22
Total Value-Weighted NYSE	6.52	7.03	8.02
NYSE Deciles 1–2	5.99	6.50	7.49

Data from 1926–2010.

The equity risk premium is calculated by subtracting the arithmetic mean of the government bond income return from the arithmetic mean of the stock market total return. Table 5-2 demonstrates this calculation for the long-horizon equity risk premium.

Table 5-2: Long-Horizon Equity Risk Premium Calculation

	Arithmetic Mean				
Long-Horizon	Market Total Return (%)		Risk-Free Rate (%)		Equity Risk Premium (%)
S&P 500	11.88	–	5.17	=	6.72*
Total Value-Weighted NYSE	11.69	–	5.17	=	6.52
NYSE Deciles 1–2	11.15	–	5.17	=	5.99*

Data from 1926–2010. *difference due to rounding.

Data for the New York Stock Exchange is obtained from Morningstar and the Center for Research in Security Prices (CRSP) at the University of Chicago's Graduate School of Business. The "Total" series is a capitalization-weighted index and includes all stocks traded on the New York Stock Exchange except closed-end mutual funds, real estate investment trusts, foreign stocks, and Americus Trusts. Capitalization-weighted means that the weight of each stock in the index, for a given month, is proportionate to its market capitalization (price times number of shares outstanding) at the beginning of that month. The "Decile 1–2" series includes all stocks with capitalizations that rank within the upper 20 percent of companies traded on the New York Stock Exchange, and it is therefore a large-capitalization index. For more information on the Center for Research in Security Pricing data methodology, see Chapter 7.

The resulting equity risk premia vary somewhat depending on the market index chosen. It is expected that using the "Total" series will result in a higher equity risk premium than using the "Decile 1–2" series, since the "Decile 1–2" series is a large-capitalization series. As of September 30, 2010, deciles 1–2 of the New York Stock Exchange contained the largest 274 companies traded on the exchange. The "Total" series includes smaller companies that have had historically higher returns, resulting in a higher equity risk premium.

The higher equity risk premium arrived at by using the S&P 500 as a market benchmark is more difficult to explain. One possible explanation is that the S&P 500 is not restricted to the largest 500 companies; other considerations such as industry composition are taken into account when determining if a company should be included in the index. Some smaller stocks are thus included, which may result in the higher equity risk premium of the index. Another possible explanation would be what is termed the "S&P inclusion effect." It is thought that simply being included among the stocks listed on the S&P 500 augments a company's returns. This is due to the large quantity of institutional funds that flow into companies that are listed in the index.

Comparing the S&P 500 total returns to those of another large-capitalization stock index may help evaluate the potential impact of the "S&P inclusion effect." Prior to March 1957, the S&P index that is used throughout this publication consisted of 90 of the largest stocks. The index composition was then changed to include 500 large-capitalization stocks that, as stated earlier, are not necessarily the 500 largest. Deciles 1–2 of the NYSE contained just over 200 of the largest companies, ranked by market capitalization, in March of 1957. The number of companies included in the deciles of the NYSE fluctuates from quarter to quarter, and by September of 2010, deciles 1–2 contained 274 companies. Though one cannot draw a causal relationship between the change in construction and the correlation of these two indices, this analysis does indicate that the "S&P inclusion effect" does not appear to be very significant in recent periods.

Another possible explanation could be differences in how survivorship is treated when calculating returns. The Center for Research in Security Prices includes the return for a company in the average decile return for the period following the company's removal from the decile, whether caused by a shift to a different decile portfolio, bankruptcy, or other such reason. On the other hand, the S&P 500 does not make this adjustment. Once a company is no longer included among the S&P 500, its return is dropped from the index. However, this effect may be lessened by the advance announcement of companies being dropped from or added to the S&P 500. In many instances throughout this publication we will present equity risk premia using both the S&P 500 and the NYSE "Deciles 1–2" portfolio to provide a comparison between these large-capitalization benchmarks.

The Market Benchmark and Firm Size

Although not restricted to include only the 500 largest companies, the S&P 500 is considered a large company index. The returns of the S&P 500 are capitalization weighted, which means that the weight of each stock in the index, for a given month, is proportionate to its market capitalization (price times number of shares outstanding) at the beginning of that month. The larger companies in the index therefore receive the majority of the weight. The use of the NYSE "Deciles 1–2" series results in an even purer large company index. Yet many valuation professionals are faced with valuing small companies, which historically have had different risk and return characteristics than large companies. If using a large stock index to calculate the equity risk premium, an adjustment is usually needed to account for the different risk and return characteristics of small stocks. This will be discussed further in Chapter 7 on the size premium.

The Risk-Free Asset

The equity risk premium can be calculated for a variety of time horizons when given the choice of risk-free asset to be used in the calculation. The *2011 Ibbotson® Stocks, Bonds, Bills, and Inflation® Classic Yearbook* provides equity risk premia calculations for short-, intermediate-, and long-term horizons. The short-, intermediate-, and long-horizon equity risk premia are calculated using the income return from a 30-day Treasury bill, a 5-year Treasury bond, and a 20-year Treasury bond, respectively.

Although the equity risk premia of several horizons are available, the long-horizon equity risk premium is preferable for use in most business-valuation settings, even if an investor has a shorter time horizon. Companies are entities that generally have no defined life span; when determining a company's value, it is important to use a long-term discount rate because the life of the company is assumed to be infinite. For this reason, it is appropriate in most cases to use the long-horizon equity risk premium for business valuation.

20-Year versus 30-Year Treasuries

Our methodology for estimating the long-horizon equity risk premium makes use of the income return on a 20-year Treasury bond; however, the Treasury currently does not issue a 20-year bond. The 30-year bond that the Treasury recently began issuing again is theoretically more correct due to the long-term nature of business valuation, yet Ibbotson Associates instead creates a series of returns using bonds on the market with approximately 20 years to maturity. The reason for the use of a 20-year maturity bond is that 30-year Treasury securities have only been issued over the relatively recent past, starting in February of 1977, and were not issued at all through the early 2000s.

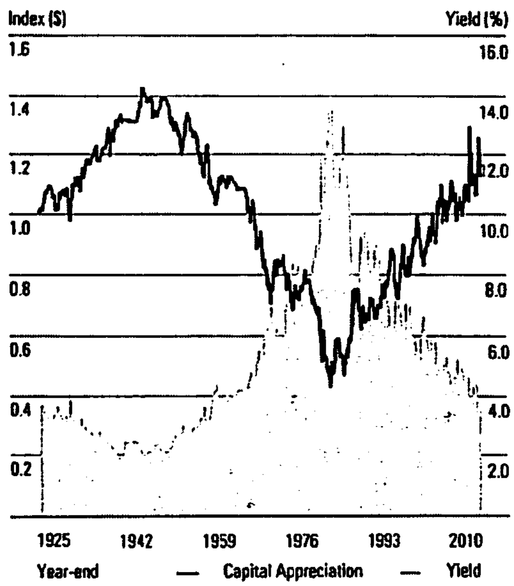
The same reason exists for why we do not use the 10-year Treasury bond—a long history of market data is not available for 10-year bonds. We have persisted in using a 20-year bond to keep the basis of the time series consistent.

Income Return

Another point to keep in mind when calculating the equity risk premium is that the income return on the appropriate-horizon Treasury security, rather than the total return, is used in the calculation. The total return is comprised of three return components: the income return, the capital appreciation return, and the reinvestment return. The income return is defined as the portion of the total return that results from a periodic cash flow or, in this case, the bond coupon payment. The capital appreciation return results from the price change of a bond over a specific period. Bond prices generally change in reaction to unexpected fluctuations in yields. Reinvestment return is the return on a given month's investment income when reinvested into the same asset class in the subsequent months of the year. The income return is thus used in the estimation of the equity risk premium because it represents the truly riskless portion of the return.[3]

Yields have generally risen on the long-term bond over the 1926–2010 period, so it has experienced negative capital appreciation over much of this time. This trend has turned around since the 1980s, however. Graph 5-1 illustrates the yields on the long-term government bond series compared to an index of the long-term government bond capital appreciation. In general, as yields rose, the capital appreciation index fell, and vice versa. Had an investor held the long-term bond to maturity, he would have realized the yield on the bond as the total return. However, in a constant maturity portfolio, such as those used to measure bond returns in this publication, bonds are sold before maturity (at a capital loss if the market yield has risen since the time of purchase). This negative return is associated with the risk of unanticipated yield changes.

Graph 5-1: Long-term Government Bond Yields versus Capital Appreciation Index



Data from 1925–2010.

For example, if bond yields rise unexpectedly, investors can receive a higher coupon payment from a newly issued bond than from the purchase of an outstanding bond with the former lower-coupon payment. The outstanding lower-coupon bond will thus fail to attract buyers, and its price will decrease, causing its yield to increase correspondingly, as its coupon payment remains the same. The newly priced outstanding bond will subsequently attract purchasers who will benefit from the shift in price and yield; however, those investors who already held the bond will suffer a capital loss due to the fall in price.

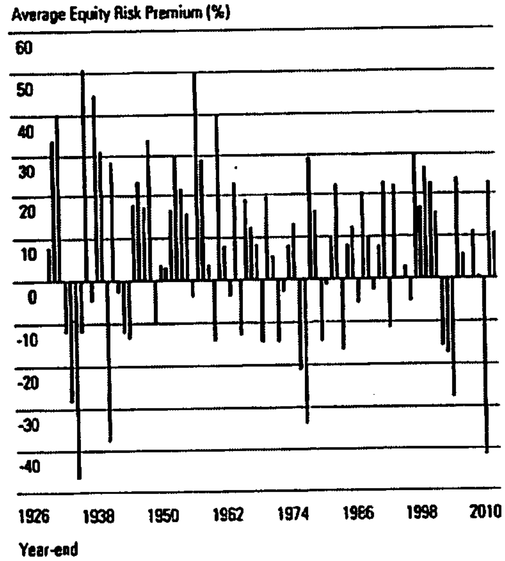
Anticipated changes in yields are assessed by the market and figured into the price of a bond. Future changes in yields that are not anticipated will cause the price of the bond to adjust accordingly. Price changes in bonds due to unanticipated changes in yields introduce price risk into the total return. Therefore, the total return on the bond series does not represent the riskless rate of return.The income return better represents the unbiased estimate of the purely riskless rate of return, since an investor can hold a bond to maturity and be entitled to the income return with no capital loss.

Arithmetic versus Geometric Means

The equity risk premium data presented in this book are arithmetic average risk premia as opposed to geometric average risk premia. The arithmetic average equity risk premium can be demonstrated to be most appropriate when discounting future cash flows. For use as the expected equity risk premium in either the CAPM or the building block approach, the arithmetic mean or the simple difference of the arithmetic means of stock market returns and riskless rates is the relevant number. This is because both the CAPM and the building block approach are additive models, in which the cost of capital is the sum of its parts. The geometric average is more appropriate for reporting past performance, since it represents the compound average return.

The argument for using the arithmetic average is quite straightforward. In looking at projected cash flows, the equity risk premium that should be employed is the equity risk premium that is expected to actually be incurred over the future time periods. Graph 5-2 shows the realized equity risk premium for each year based on the returns of the S&P 500 and the income return on long-term government bonds. (The actual, observed difference between the return on the stock market and the riskless rate is known as the realized equity risk premium.) There is considerable volatility in the year-by-year statistics. At times the realized equity risk premium is even negative.

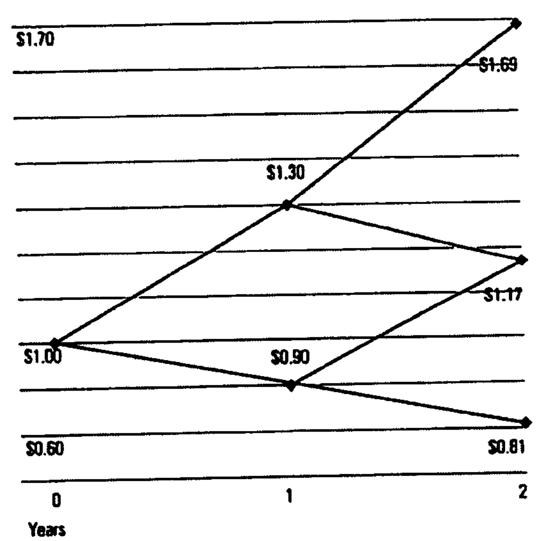
Graph 5-2: Realized Equity Risk Premium Per Year



Data from 1926–2010.

To illustrate how the arithmetic mean is more appropriate than the geometric mean in discounting cash flows, suppose the expected return on a stock is 10 percent per year with a standard deviation of 20 percent. Also assume that only two outcomes are possible each year: +30 percent and –10 percent (i.e., the mean plus or minus one standard deviation). The probability of occurrence for each outcome is equal. The growth of wealth over a two-year period is illustrated in Graph 5-3.

Graph 5-3: Growth of Wealth Example



The most common outcome of $1.17 is given by the geometric mean of 8.2 percent. Compounding the possible outcomes as follows derives the geometric mean:

$$\left[(1+0.30)\times(1-0.10)\right]^{1/2}-1=0.082$$

However, the expected value is predicted by compounding the arithmetic, not the geometric, mean. To illustrate this, we need to look at the probability-weighted average of all possible outcomes:

(0.25 × $1.69) =	$0.4225
+ (0.50 × $1.17) =	$0.5850
+ (0.25 × $0.81) =	$0.2025
Total	$1.2100

Therefore, $1.21 is the probability-weighted expected value. The rate that must be compounded to achieve the terminal value of $1.21 after 2 years is 10 percent, the arithmetic mean:

$$\$1\times(1+0.10)^2=\$1.21$$

The geometric mean, when compounded, results in the median of the distribution:

$$\$1\times(1+0.082)^2=\$1.17$$

The arithmetic mean equates the expected future value with the present value; it is therefore the appropriate discount rate.

Appropriate Historical Time Period

The equity risk premium can be estimated using any historical time period. For the U.S., market data exists at least as far back as the late 1800s. Therefore, it is possible to estimate the equity risk premium using data that covers roughly the past 100 years.

Our equity risk premium covers the time period from 1926 to the present. The original data source for the time series comprising the equity risk premium is the Center for Research in Security Prices. CRSP chose to begin their analysis of market returns with 1926 for two main reasons. CRSP determined that the time period around 1926 was approximately when quality financial data became available. They also made a conscious effort to include the period of extreme market volatility from the late twenties and early thirties; 1926 was chosen because it includes one full business cycle of data before the market crash of 1929. These are the most basic reasons why our equity risk premium calculation window starts in 1926.

Implicit in using history to forecast the future is the assumption that investors' expectations for future outcomes conform to past results. This method assumes that the price of taking on risk changes only slowly, if at all, over time. This "future equals the past" assumption is most applicable to a random time-series variable. A time-series variable is random if its value in one period is independent of its value in other periods.

Does the Equity Risk Premium Revert to Its Mean Over Time?

Some have argued that the estimate of the equity risk premium is upwardly biased since the stock market is currently priced high. In other words, since there have been several years with extraordinarily high market returns and realized equity risk premia, the expectation is that returns and realized equity risk premia will be lower in the future, bringing the average back to a normalized level. This argument relies on several studies that have tried to determine whether reversion to the mean exists in stock market prices and the equity risk premium.[3] Several academics contradict each other on this topic; moreover, the evidence supporting this argument is neither conclusive nor compelling enough to make such a strong assumption.

Our own empirical evidence suggests that the yearly difference between the stock market total return and the U.S. Treasury bond income return in any particular year is random. Graph 5-2, presented earlier, illustrates the randomness of the realized equity risk premium.

A statistical measure of the randomness of a return series is its serial correlation. Serial correlation (or autocorrelation) is defined as the degree to which the return of a given series is related from period to period. A serial correlation near positive one indicates that returns are predictable from one period to the next period and are positively related. That is, the returns of one period are a good predictor of the returns in the next period. Conversely, a serial correlation near negative one indicates that the returns in one period are inversely related to those of the next period. A serial correlation near zero indicates that the returns are random or unpredictable from one period to the next. Table 5-3 contains the serial correlation of the market total returns, the realized long-horizon equity risk premium, and inflation.

Table 5-3: Interpretation of Annual Serial Correlations

Series	Serial Correlation	Interpretation
Large Company Stock Total Returns	0.02	Random
Equity Risk Premium	0.02	Random
Inflation Rates	0.64	Trend

Data from 1926–2010.

The significance of this evidence is that the realized equity risk premium next year will not be dependent on the realized equity risk premium from this year. That is, there is no discernable pattern in the realized equity risk premium—it is virtually impossible to forecast next year's realized risk premium based on the premium of the previous year. For example, if this year's difference between the riskless rate and the return on the stock market is higher than last year's, that does not imply that next year's will be higher than this year's. It is as likely to be higher as it is lower. The best estimate of the expected value of a variable that has behaved randomly in the past is the average (or arithmetic mean) of its past values.

Table 5-4 also indicates that the equity risk premium varies considerably by decade. The complete decades ranged from a high of 17.9 percent in the 1950s to a low of -3.7 percent in the 2000s. This look at historical equity risk premium reveals no observable pattern.

Table 5-4: Long-Horizon Equity Risk Premium by Decade (%)

1920s*	1930s	1940s	1950s	1960s	1970s	1980s	1990s	2000s	2001-2010
17.6	2.3	8.0	17.9	4.2	0.3	7.9	12.1	-3.7	-1.1

Data from 1926–2010.
*Based on the period 1926–1929.

Finnerty and Leistikow perform more econometrically sophisticated tests of mean reversion in the equity risk premium. Their tests demonstrate that—as we suspected from our simpler tests—the equity risk premium that was realized over 1926 to the present was almost perfectly free of mean reversion and had no statistically identifiable time trends.[4] Lo and MacKinlay conclude, "the rejection of the random walk for weekly returns does not support a mean-reverting model of asset prices."

Choosing an Appropriate Historical Period

The estimate of the equity risk premium depends on the length of the data series studied. A proper estimate of the equity risk premium requires a data series long enough to give a reliable average without being unduly influenced by very good and very poor short-term returns. When calculated using a long data series, the historical equity risk premium is relatively stable.[5] Furthermore, because an average of the realized equity risk premium is quite volatile when calculated using a short history, using a long series makes it less likely that the analyst can justify any number he or she wants. The magnitude of how shorter periods can affect the result will be explored later in this chapter.

Some analysts estimate the expected equity risk premium using a shorter, more recent time period on the basis that recent events are more likely to be repeated in the near future; furthermore, they believe that the 1920s, 1930s, and 1940s contain too many unusual events. This view is suspect because all periods contain "unusual" events. Some of the most unusual events of the last hundred years took place quite recently, including the inflation of the late 1970s and early 1980s, the October 1987 stock market crash, the collapse of the high-yield bond market, the major contraction and consolidation of the thrift industry, the collapse of the Soviet Union, the development of the European Economic Community, the attacks of September 11, 2001 and the more recent liquidity crisis of 2008 and 2009.

It is even difficult for economists to predict the economic environment of the future. For example, if one were analyzing the stock market in 1987 before the crash, it would be statistically improbable to predict the impending short-term volatility without considering the stock market crash and market volatility of the 1929–1931 period. Without an appreciation of the 1920s and 1930s, no one would believe that such events could happen. The 85-year period starting with 1926 is representative of what can happen: it includes high and low returns, volatile and quiet markets, war and peace, inflation and deflation, and prosperity and depression. Restricting attention to a shorter historical period underestimates the amount of change that could occur in a long future period. Finally, because historical event-types (not specific events) tend to repeat themselves, long-run capital market return studies can reveal a great deal about the future. Investors probably expect "unusual" events to occur from time to time, and their return expectations reflect this.

A Look at the Historical Results

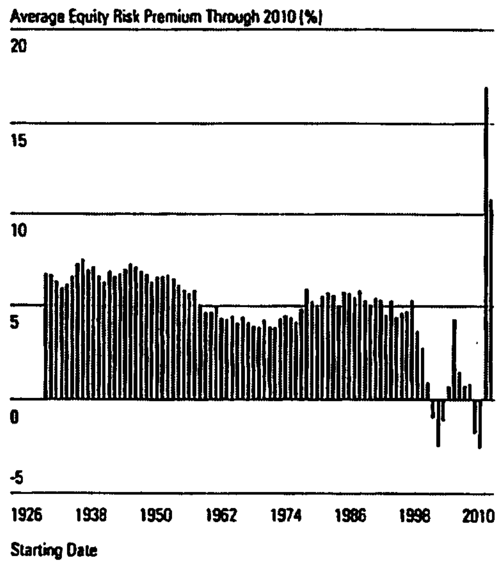
It is interesting to take a look at the realized returns and realized equity risk premium in the context of the above discussion. Table 5-5 shows the average stock market return and the average (arithmetic mean) realized long-horizon equity risk premium over various historical time periods. Similarly, Graph 5-5 shows the average (arithmetic mean) realized equity risk premium calculated through 2010 for different ending dates. The table and the graph both show that using a longer historical period provides a more stable estimate of the equity risk premium. The reason is that any unique period will not be weighted heavily in an average covering a longer historical period. It better represents the probability of these unique events occurring over a long period of time.

Table 5-5: Stock Market Return and Equity Risk Premium Over Time

Length (Yrs.)	Period Dates	Large Company Stock Arithmetic Mean Total Return (%)	Long-Horizon Equity Risk Premium (%)
85	1926–2010	11.8	6.7
70	1941–2010	12.6	7.0
60	1951–2010	12.3	6.1
50	1961–2010	11.2	4.4
40	1971–2010	11.8	4.5
30	1981–2010	12.2	5.0
20	1991–2010	11.0	5.3
15	1996–2010	8.9	3.7
10	2001–2010	3.6	-1.1
5	2006–2010	5.2	0.8

Data from 1926–2010.

Graph 5-4: Equity Risk Premium Using Different Starting Dates



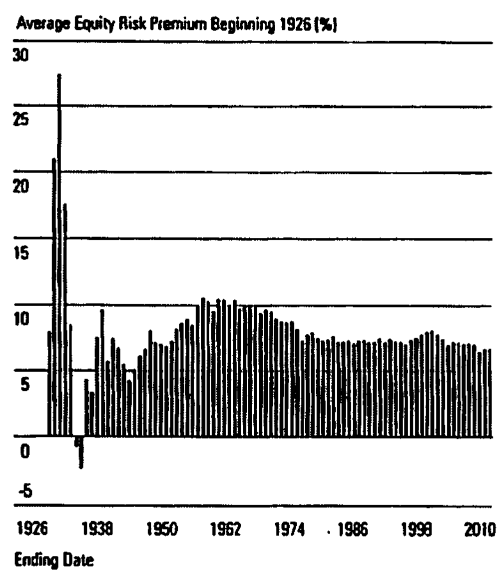
Data from 1926–2010.

Looking carefully at Graph 5-4 will clarify this point. The graph shows the realized equity risk premium for a series of time periods through 2010, starting with 1926. In other words, the first value on the graph represents the average realized equity risk premium over the period 1926–2010. The next value on the graph represents the average realized equity risk premium over the period 1927–2010, and so on, with the last value representing the average over the most recent five years, 2006–2010. Concentrating on the left side of Graph 5-5, one notices that the realized equity risk premium, when measured over long periods of time, is relatively stable. In viewing the graph from left to right, moving from longer to shorter historical periods, one sees that the value of the realized equity risk premium begins to decline significantly. Why does this occur? The reason is that the severe bear market of 1973–1974 is receiving proportionately more weight in the shorter, more recent average. If you continue to follow the line to the right, however, you will also notice that when 1973 and 1974 fall out of the recent average, the realized equity risk premium jumps up by nearly 1.2 percent.

Additionally, use of recent historical periods for estimation purposes can lead to illogical conclusions. As seen in Table 5-5, the bear market in the early 2000's and in 2008 has caused the realized equity risk premium in the shorter historical periods to be lower than the long-term average.

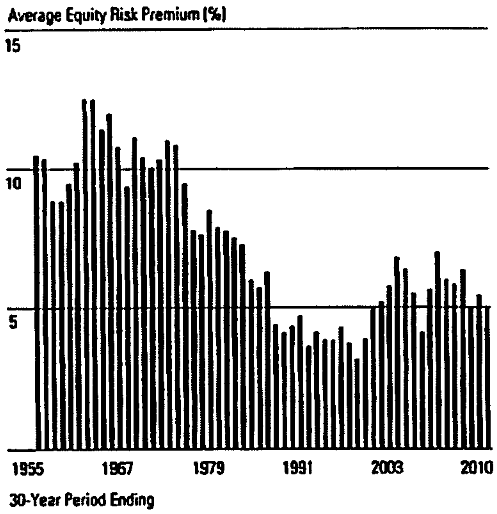
The impact of adding one additional year of data to a historical average is lessened the greater the initial time period of measurement. Short-term averages can be affected considerably by one or more unique observations. On the other hand, long-term averages produce more stable results. A series of graphs looking at the realized equity risk premium will illustrate this effect. Graph 5-5 shows the average (arithmetic mean) realized long-horizon equity risk premium starting in 1926. Each additional point on the graph represents the addition of another year to the average. Although the graph is extremely volatile in the beginning periods, the stability of the long-term average is quite remarkable. Again, the "unique" periods of time will not be weighted heavily in a long-term average, resulting in a more stable estimate.

Graph 5-5: Equity Risk Premium Using Different Ending Dates



Data from 1926–2010.

Graph 5-6: Equity Risk Premium Over 30-Year Periods



Data from 1926–2010.

Some practitioners argue for a shorter historical time period, such as 30 years, as a basis for the equity risk premium estimation. The logic for the use of a shorter period is that historical events and economic scenarios present before this time are unlikely to be repeated. Graph 5-6 shows the equity risk premium measured over 30-year periods, and it appears from the graph that the premium has been trending downwards. The 30-year equity risk premium remained close to 4 percent for several years in the 1980s and 1990s. However, it has fallen and then risen in the most recent 30-year periods.

The key to understanding this result lies again in the years 1973 and 1974. The oil embargo during this period had a tremendous effect on the market. The equity risk premium for these years alone was -21 and -34 percent, respectively. Periods that include the years 1973 and 1974 result in an average equity risk premium as low as 3.1 percent. In the most recent 30-year periods that excludes 1973 and 1974, the average rises to over 6 percent. The 2000s have also had an enormous effect on the equity risk premium.

It is difficult to justify such a large divergence in estimates of return over such a short period of time. This does not suggest, however, that the years 1973 and 1974 should be excluded from any estimate of the equity risk premium; rather, it emphasizes the importance of using a long historical period when measuring the equity risk premium in order to obtain a reliable average that is not overly influenced by short-term returns. The same holds true when analyzing the poor performance of the early 2000s and 2008.

Does the Equity Risk Premium Represent Minority or Controlling Interest?

There is quite a bit of confusion among valuation practitioners regarding the use of publicly traded company data to derive the equity risk premium. Is a minority discount implicit in this data? Recall that the equity risk premium is typically derived from the returns of a market index: the S&P 500, the New York Stock Exchange (NYSE), or the NYSE Deciles 1–2. (The size premia that are covered in Chapter 7 are derived from the returns of companies traded on the NYSE, in addition to those on the NYSE AMEX and NASDAQ). Both the S&P 500 and the NYSE include a preponderance of companies that are minority held. Does this imply that an equity risk premium (or size premium) derived from these data represents a minority interest premium? This is a critical issue that must be addressed by the valuation professional, since applying a minority discount or a control premium can have a material impact on the ultimate value derived in an appraisal.

Since most companies in the S&P 500 and the NYSE are minority held, some assume that the risk premia derived from these return data represent minority returns and therefore have a minority discount implicit within them. However, this assumption is not correct. The returns that are generated by the S&P 500 and the NYSE represent returns to equity holders. While most of these companies are minority held, there is no evidence that higher rates of return could be earned if these companies were suddenly acquired by majority shareholders. The equity risk premium represents expected premiums that holders of securities of a similar nature can expect to achieve on average into the future. There is no distinction between minority owners and controlling owners.

The discount rate is meant to represent the underlying risk of being in a particular industry or line of business. There are instances when a majority shareholder can acquire a company and improve the cash flows generated by that company. However, this does not necessarily have an impact on the general risk level of the cash flows generated by the company.

Carolina Water Service, Inc.
ORS Witness Dr. Gordon's CAPM Analysis Corrected to Reflect Arithmetic Mean Historical Total Returns and the Empirical CAPM

Calculation of Long-Run Average Return

Decile	Total Return
1	10.9 %
2	12.9
3	13.6
4	13.9
5	14.8
6	15.0
7	15.4
8	16.5
9	17.2
10	21.0
Average	15.1 %

Source of Information: Ibbotson® SBBI® 2011 Classis Yearbook - Market Results for Stocks, Bonds, Bills, and Inflation 1926-2010, Morningstar, Inc., 2011 Chicago, IL, p. 94.

Carolina Water Service, Inc.
ORS Witness Dr. Gordon's CAPM Analysis Corrected to Reflect Arithmetic Mean Historical Total Returns and the Empirical CAPM

Line No.		Traditional CAPM	
1.	Expected Market Return	15.10	% (1)
2.	Forecasted Risk-Free Rate	(5.00)	(2)
3.	Forecasted Market Equity Risk Premium	10.10	%
4.	Proxy Group Beta	0.7222	(2)
5.	Proxy Group Specific Equity Risk Premium	7.29	%
6.	Risk-Free Rate	5.00	(2)
7.	Traditional CAPM Result	12.29	%
		Empirical CAPM	
8.	Forecasted Market Equity Risk Premium	10.10	% (1)
9.	Proxy Group Beta	0.7222	(2)
10.	Proxy Group Specific Equity Risk Premium	8.00	% (3)
11.	Risk-Free Rate	5.00	(2)
12.	Empirical CAPM Result	13.00	%
13.	Average of Traditional & Empirical CAPM	12.65	%
14.	ORS Witness Carlisle's CAPM Result	9.48	% (2)

Notes:
(1) From page 1 of this Schedule.
(2) From Exhibit DHC-9, page 2.
(3) ECAPM formula derived on Exhibit No. ___, Schedule PMA-10, page 3 of 3, Note 4.

NEW

REGULATORY

FINANCE

Roger A. Morin, PhD

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The model is analogous to the standard CAPM, but with the return on a minimum risk portfolio that is unrelated to market returns, R_Z, replacing the risk-free rate, R_F. The model has been empirically tested by Black, Jensen, and Scholes (1972), who find a flatter than predicted SML, consistent with the model and other researchers' findings. An updated version of the Black-Jensen-Scholes study is available in Brealey, Myers, and Allen (2006) and reaches similar conclusions.

The zero-beta CAPM cannot be literally employed to estimate the cost of capital, since the zero-beta portfolio is a statistical construct difficult to replicate. Attempts to estimate the model are formally equivalent to estimating the constants, a and b, in Equation 6-2. A practical alternative is to employ the Empirical CAPM, to which we now turn.

6.3 Empirical CAPM

As discussed in the previous section, several finance scholars have developed refined and expanded versions of the standard CAPM by relaxing the constraints imposed on the CAPM, such as dividend yield, size, and skewness effects. These enhanced CAPMs typically produce a risk-return relationship that is flatter than the CAPM prediction in keeping with the actual observed risk-return relationship. The ECAPM makes use of these empirical findings. The ECAPM estimates the cost of capital with the equation:

$$K = R_F + \alpha + \beta \times (MRP - \alpha) \qquad (6\text{-}5)$$

where α is the "alpha" of the risk-return line, a constant, and the other symbols are defined as before. All the potential vagaries of the CAPM are telescoped into the constant α, which must be estimated econometrically from market data. Table 6-2 summarizes[10] the empirical evidence on the magnitude of alpha.[11]

[10] The technique is formally applied by Litzenberger, Ramaswamy, and Sosin (1980) to public utilities in order to rectify the CAPM's basic shortcomings. Not only do they summarize the criticisms of the CAPM insofar as they affect public utilities, but they also describe the econometric intricacies involved and the methods of circumventing the statistical problems. Essentially, the average monthly returns over a lengthy time period on a large cross-section of securities grouped into portfolios are related to their corresponding betas by statistical regression techniques; that is, Equation 6-5 is estimated from market data. The utility's beta value is substituted into the equation to produce the cost of equity figure. Their own results demonstrate how the standard CAPM underestimates the cost of equity capital of public utilities because of utilities' high dividend yield and return skewness.

[11] Adapted from Vilbert (2004).

TABLE 6-2
EMPIRICAL EVIDENCE ON THE ALPHA FACTOR

Author	Range of alpha
Fischer (1993)	−3.6% to 3.6%
Fischer, Jensen and Scholes (1972)	−9.61% to 12.24%
Fama and McBeth (1972)	4.08% to 9.36%
Fama and French (1992)	10.08% to 13.56%
Litzenberger and Ramaswamy (1979)	5.32% to 8.17%
Litzenberger, Ramaswamy and Sosin (1980)	1.63% to 5.04%
Pettengill, Sundaram and Mathur (1995)	4.6%
Morin (1989)	2.0%

For an alpha in the range of 1%–2% and for reasonable values of the market risk premium and the risk-free rate, Equation 6-5 reduces to the following more pragmatic form:

$$K = R_F + 0.25\ (R_M - R_F) + 0.75\ \beta(R_M - R_F) \qquad (6\text{-}6)$$

Over reasonable values of the risk-free rate and the market risk premium, Equation 6-6 produces results that are indistinguishable from the ECAPM of Equation 6-5.[12]

An alpha range of 1%–2% is somewhat lower than that estimated empirically. The use of a lower value for alpha leads to a lower estimate of the cost of capital for low-beta stocks such as regulated utilities. This is because the use of a long-term risk-free rate rather than a short-term risk-free rate already incorporates some of the desired effect of using the ECAPM. That is, the

[12] Typical of the empirical evidence on the validity of the CAPM is a study by Morin (1989) who found that the relationship between the expected return on a security and beta over the period 1926–1984 was given by:

$$\text{Return} = 0.0829 + 0.0520\ \beta$$

Given that the risk-free rate over the estimation period was approximately 6% and that the market risk premium was 8% during the period of study, the intercept of the observed relationship between return and beta exceeds the risk-free rate by about 2%, or 1/4 of 8%, and that the slope of the relationship is close to 3/4 of 8%. Therefore, the empirical evidence suggests that the expected return on a security is related to its risk by the following approximation:

$$K = R_F + x(R_M - R_F) + (1 - x)\beta(R_M - R_F)$$

where x is a fraction to be determined empirically. The value of x that best explains the observed relationship Return = 0.0829 + 0.0520 β is between 0.25 and 0.30. If x = 0.25, the equation becomes:

$$K = R_F + 0.25(R_M - R_F) + 0.75\beta(R_M - R_F)$$

long-term risk-free rate version of the CAPM has a higher intercept and a flatter slope than the short-term risk-free version which has been tested. Thus, it is reasonable to apply a conservative alpha adjustment. Moreover, the lowering of the tax burden on capital gains and dividend income enacted in 2002 may have decreased the required return for taxable investors, steepening the slope of the ECAPM risk-return trade-off and bring it closer to the CAPM predicted returns.[13]

To illustrate the application of the ECAPM, assume a risk-free rate of 5%, a market risk premium of 7%, and a beta of 0.80. The Empirical CAPM equation (6-6) above yields a cost of equity estimate of 11.0% as follows:

$$\begin{aligned} K &= 5\% + 0.25\,(12\% - 5\%) + 0.75 \times 0.80\,(12\% - 5\%) \\ &= 5.0\% + 1.8\% + 4.2\% \\ &= 11.0\% \end{aligned}$$

As an alternative to specifying alpha, see Example 6-1.

Some have argued that the use of the ECAPM is inconsistent with the use of adjusted betas, such as those supplied by Value Line and Bloomberg. This is because the reason for using the ECAPM is to allow for the tendency of betas to regress toward the mean value of 1.00 over time, and, since Value Line betas are already adjusted for such trend, an ECAPM analysis results in double-counting. This argument is erroneous. Fundamentally, the ECAPM is not an adjustment, increase or decrease, in beta. This is obvious from the fact that the expected return on high beta securities is actually lower than that produced by the CAPM estimate. The ECAPM is a formal recognition that the observed risk-return tradeoff is flatter than predicted by the CAPM based on myriad empirical evidence. The ECAPM and the use of adjusted betas comprised two separate features of asset pricing. Even if a company's beta is estimated accurately, the CAPM still understates the return for low-beta stocks. Even if the ECAPM is used, the return for low-beta securities is understated if the betas are understated. Referring back to Figure 6-1, the ECAPM is a return (vertical axis) adjustment and not a beta (horizontal axis) adjustment. Both adjustments are necessary. Moreover, recall from Chapter 3 that the use of adjusted betas compensates for interest rate sensitivity of utility stocks not captured by unadjusted betas.

[13] The lowering of the tax burden on capital gains and dividend income has no impact as far as non-taxable institutional investors (pension funds, 401K, and mutual funds) are concerned, and such investors engage in very large amounts of trading on security markets. It is quite plausible that taxable retail investors are relatively inactive traders and that large non-taxable investors have a substantial influence on capital markets.

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The Capital Asset Pricing Model: Theory and Evidence

Eugene F. Fama and Kenneth R. French

The capital asset pricing model (CAPM) of William Sharpe (1964) and John Lintner (1965) marks the birth of asset pricing theory (resulting in a Nobel Prize for Sharpe in 1990). Four decades later, the CAPM is still widely used in applications, such as estimating the cost of capital for firms and evaluating the performance of managed portfolios. It is the centerpiece of MBA investment courses. Indeed, it is often the only asset pricing model taught in these courses.[1]

The attraction of the CAPM is that it offers powerful and intuitively pleasing predictions about how to measure risk and the relation between expected return and risk. Unfortunately, the empirical record of the model is poor—poor enough to invalidate the way it is used in applications. The CAPM's empirical problems may reflect theoretical failings, the result of many simplifying assumptions. But they may also be caused by difficulties in implementing valid tests of the model. For example, the CAPM says that the risk of a stock should be measured relative to a comprehensive "market portfolio" that in principle can include not just traded financial assets, but also consumer durables, real estate and human capital. Even if we take a narrow view of the model and limit its purview to traded financial assets, is it

[1] Although every asset pricing model is a capital asset pricing model, the finance profession reserves the acronym CAPM for the specific model of Sharpe (1964), Lintner (1965) and Black (1972) discussed here. Thus, throughout the paper we refer to the Sharpe-Lintner-Black model as the CAPM.

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legitimate to limit further the market portfolio to U.S. common stocks (a typical choice), or should the market be expanded to include bonds, and other financial assets, perhaps around the world? In the end, we argue that whether the model's problems reflect weaknesses in the theory or in its empirical implementation, the failure of the CAPM in empirical tests implies that most applications of the model are invalid.

We begin by outlining the logic of the CAPM, focusing on its predictions about risk and expected return. We then review the history of empirical work and what it says about shortcomings of the CAPM that pose challenges to be explained by alternative models.

The Logic of the CAPM

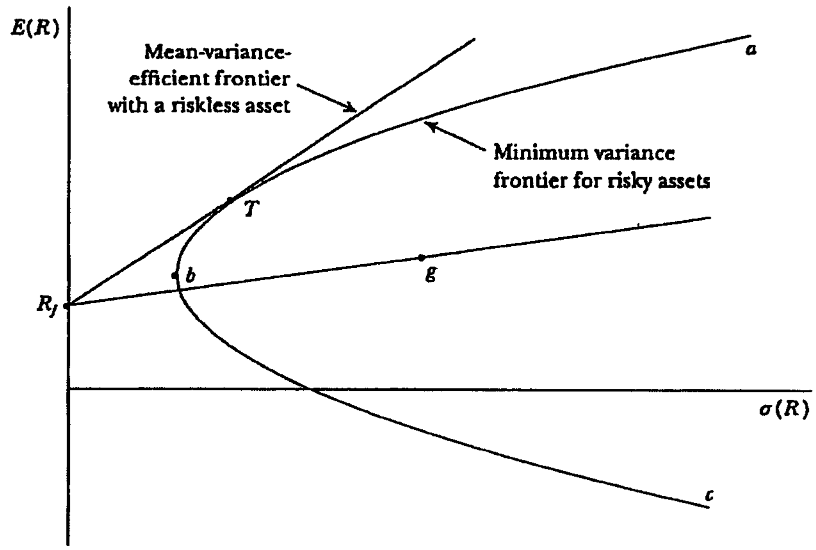
The CAPM builds on the model of portfolio choice developed by Harry Markowitz (1959). In Markowitz's model, an investor selects a portfolio at time $t - 1$ that produces a stochastic return at t. The model assumes investors are risk averse and, when choosing among portfolios, they care only about the mean and variance of their one-period investment return. As a result, investors choose "mean-variance-efficient" portfolios, in the sense that the portfolios 1) minimize the variance of portfolio return, given expected return, and 2) maximize expected return, given variance. Thus, the Markowitz approach is often called a "mean-variance model."

The portfolio model provides an algebraic condition on asset weights in mean-variance-efficient portfolios. The CAPM turns this algebraic statement into a testable prediction about the relation between risk and expected return by identifying a portfolio that must be efficient if asset prices are to clear the market of all assets.

Sharpe (1964) and Lintner (1965) add two key assumptions to the Markowitz model to identify a portfolio that must be mean-variance-efficient. The first assumption is *complete agreement*: given market clearing asset prices at $t - 1$, investors agree on the joint distribution of asset returns from $t - 1$ to t. And this distribution is the true one—that is, it is the distribution from which the returns we use to test the model are drawn. The second assumption is that there is *borrowing and lending at a risk-free rate*, which is the same for all investors and does not depend on the amount borrowed or lent.

Figure 1 describes portfolio opportunities and tells the CAPM story. The horizontal axis shows portfolio risk, measured by the standard deviation of portfolio return; the vertical axis shows expected return. The curve *abc*, which is called the minimum variance frontier, traces combinations of expected return and risk for portfolios of risky assets that minimize return variance at different levels of expected return. (These portfolios do not include risk-free borrowing and lending.) The tradeoff between risk and expected return for minimum variance portfolios is apparent. For example, an investor who wants a high expected return, perhaps at point *a*, must accept high volatility. At point *T*, the investor can have an interme-

Figure 1
Investment Opportunities



diate expected return with lower volatility. If there is no risk-free borrowing or lending, only portfolios above b along abc are mean-variance-efficient, since these portfolios also maximize expected return, given their return variances.

Adding risk-free borrowing and lending turns the efficient set into a straight line. Consider a portfolio that invests the proportion x of portfolio funds in a risk-free security and $1 - x$ in some portfolio g. If all funds are invested in the risk-free security—that is, they are loaned at the risk-free rate of interest—the result is the point R_f in Figure 1, a portfolio with zero variance and a risk-free rate of return. Combinations of risk-free lending and positive investment in g plot on the straight line between R_f and g. Points to the right of g on the line represent borrowing at the risk-free rate, with the proceeds from the borrowing used to increase investment in portfolio g. In short, portfolios that combine risk-free lending or borrowing with some risky portfolio g plot along a straight line from R_f through g in Figure 1.[2]

[2] Formally, the return, expected return and standard deviation of return on portfolios of the risk-free asset f and a risky portfolio g vary with x, the proportion of portfolio funds invested in f, as

$$R_p = xR_f + (1 - x)R_g,$$

$$E(R_p) = xR_f + (1 - x)E(R_g),$$

$$\sigma(R_p) = (1 - x)\sigma(R_g),\ x \leq 1.0,$$

which together imply that the portfolios plot along the line from R_f through g in Figure 1.

To obtain the mean-variance-efficient portfolios available with risk-free borrowing and lending, one swings a line from R_f in Figure 1 up and to the left as far as possible, to the tangency portfolio T. We can then see that all efficient portfolios are combinations of the risk-free asset (either risk-free borrowing or lending) and a single risky tangency portfolio, T. This key result is Tobin's (1958) "separation theorem."

The punch line of the CAPM is now straightforward. With complete agreement about distributions of returns, all investors see the same opportunity set (Figure 1), and they combine the same risky tangency portfolio T with risk-free lending or borrowing. Since all investors hold the same portfolio T of risky assets, it must be the value-weight market portfolio of risky assets. Specifically, each risky asset's weight in the tangency portfolio, which we now call M (for the "market"), must be the total market value of all outstanding units of the asset divided by the total market value of all risky assets. In addition, the risk-free rate must be set (along with the prices of risky assets) to clear the market for risk-free borrowing and lending.

In short, the CAPM assumptions imply that the market portfolio M must be on the minimum variance frontier if the asset market is to clear. This means that the algebraic relation that holds for any minimum variance portfolio must hold for the market portfolio. Specifically, if there are N risky assets,

$$\text{(Minimum Variance Condition for } M\text{)} \quad E(R_i) = E(R_{ZM}) + [E(R_M) - E(R_{ZM})]\beta_{iM}, \; i = 1, \ldots, N.$$

In this equation, $E(R_i)$ is the expected return on asset i, and β_{iM}, the market beta of asset i, is the covariance of its return with the market return divided by the variance of the market return,

$$\text{(Market Beta)} \quad \beta_{iM} = \frac{\mathrm{cov}(R_i, R_M)}{\sigma^2(R_M)}.$$

The first term on the right-hand side of the minimum variance condition, $E(R_{ZM})$, is the expected return on assets that have market betas equal to zero, which means their returns are uncorrelated with the market return. The second term is a risk premium—the market beta of asset i, β_{iM}, times the premium per unit of beta, which is the expected market return, $E(R_M)$, minus $E(R_{ZM})$.

Since the market beta of asset i is also the slope in the regression of its return on the market return, a common (and correct) interpretation of beta is that it measures the sensitivity of the asset's return to variation in the market return. But there is another interpretation of beta more in line with the spirit of the portfolio model that underlies the CAPM. The risk of the market portfolio, as measured by the variance of its return (the denominator of β_{iM}), is a weighted average of the covariance risks of the assets in M (the numerators of β_{iM} for different assets).

Thus, β_{iM} is the covariance risk of asset i in M measured relative to the average covariance risk of assets, which is just the variance of the market return.[3] In economic terms, β_{iM} is proportional to the risk each dollar invested in asset i contributes to the market portfolio.

The last step in the development of the Sharpe-Lintner model is to use the assumption of risk-free borrowing and lending to nail down $E(R_{ZM})$, the expected return on zero-beta assets. A risky asset's return is uncorrelated with the market return—its beta is zero—when the average of the asset's covariances with the returns on other assets just offsets the variance of the asset's return. Such a risky asset is riskless in the market portfolio in the sense that it contributes nothing to the variance of the market return.

When there is risk-free borrowing and lending, the expected return on assets that are uncorrelated with the market return, $E(R_{ZM})$, must equal the risk-free rate, R_f. The relation between expected return and beta then becomes the familiar Sharpe-Lintner CAPM equation,

$$\text{(Sharpe-Lintner CAPM)} \quad E(R_i) = R_f + [E(R_M) - R_f)]\beta_{iM},\ i = 1, \ldots, N.$$

In words, the expected return on any asset i is the risk-free interest rate, R_f, plus a risk premium, which is the asset's market beta, β_{iM}, times the premium per unit of beta risk, $E(R_M) - R_f$.

Unrestricted risk-free borrowing and lending is an unrealistic assumption. Fischer Black (1972) develops a version of the CAPM without risk-free borrowing or lending. He shows that the CAPM's key result—that the market portfolio is mean-variance-efficient—can be obtained by instead allowing unrestricted short sales of risky assets. In brief, back in Figure 1, if there is no risk-free asset, investors select portfolios from along the mean-variance-efficient frontier from a to b. Market clearing prices imply that when one weights the efficient portfolios chosen by investors by their (positive) shares of aggregate invested wealth, the resulting portfolio is the market portfolio. The market portfolio is thus a portfolio of the efficient portfolios chosen by investors. With unrestricted short selling of risky assets, portfolios made up of efficient portfolios are themselves efficient. Thus, the market portfolio is efficient, which means that the minimum variance condition for M given above holds, and it is the expected return-risk relation of the Black CAPM.

The relations between expected return and market beta of the Black and Sharpe-Lintner versions of the CAPM differ only in terms of what each says about $E(R_{ZM})$, the expected return on assets uncorrelated with the market. The Black version says only that $E(R_{ZM})$ must be less than the expected market return, so the

[3] Formally, if x_{iM} is the weight of asset i in the market portfolio, then the variance of the portfolio's return is

$$\sigma^2(R_M) = Cov(R_M, R_M) = Cov\left(\sum_{i=1}^{N} x_{iM}R_i,\ R_M\right) = \sum_{i=1}^{N} x_{iM}Cov(R_i, R_M).$$

premium for beta is positive. In contrast, in the Sharpe-Lintner version of the model, $E(R_{ZM})$ must be the risk-free interest rate, R_f, and the premium per unit of beta risk is $E(R_M) - R_f$.

The assumption that short selling is unrestricted is as unrealistic as unrestricted risk-free borrowing and lending. If there is no risk-free asset and short sales of risky assets are not allowed, mean-variance investors still choose efficient portfolios—points above *b* on the *abc* curve in Figure 1. But when there is no short selling of risky assets and no risk-free asset, the algebra of portfolio efficiency says that portfolios made up of efficient portfolios are not typically efficient. This means that the market portfolio, which is a portfolio of the efficient portfolios chosen by investors, is not typically efficient. And the CAPM relation between expected return and market beta is lost. This does not rule out predictions about expected return and betas with respect to other efficient portfolios—if theory can specify portfolios that must be efficient if the market is to clear. But so far this has proven impossible.

In short, the familiar CAPM equation relating expected asset returns to their market betas is just an application to the market portfolio of the relation between expected return and portfolio beta that holds in any mean-variance-efficient portfolio. The efficiency of the market portfolio is based on many unrealistic assumptions, including complete agreement and either unrestricted risk-free borrowing and lending or unrestricted short selling of risky assets. But all interesting models involve unrealistic simplifications, which is why they must be tested against data.

Early Empirical Tests

Tests of the CAPM are based on three implications of the relation between expected return and market beta implied by the model. First, expected returns on all assets are linearly related to their betas,[4] and no other variable has marginal explanatory power. Second, the beta premium is positive, meaning that the expected return on the market portfolio exceeds the expected return on assets whose returns are uncorrelated with the market return. Third, in the Sharpe-Lintner version of the model, assets uncorrelated with the market have expected returns equal to the risk-free interest rate, and the beta premium is the expected market return minus the risk-free rate. Most tests of these predictions use either cross-section or time-series regressions. Both approaches date to early tests of the model.

Tests on Risk Premiums

The early cross-section regression tests focus on the Sharpe-Lintner model's predictions about the intercept and slope in the relation between expected return and market beta. The approach is to regress a cross-section of average asset returns on estimates of asset betas. The model predicts that the intercept in these regressions is the risk-free interest rate, R_f, and the coefficient on beta is the expected return on the market in excess of the risk-free rate, $E(R_M) - R_f$.

Two problems in these tests quickly became apparent. First, estimates of beta for individual assets are imprecise, creating a measurement error problem when they are used to explain average returns. Second, the regression residuals have common sources of variation, such as industry effects in average returns. Positive correlation in the residuals produces downward bias in the usual ordinary least squares estimates of the standard errors of the cross-section regression slopes.

To improve the precision of estimated betas, researchers such as Blume (1970), Friend and Blume (1970) and Black, Jensen and Scholes (1972) work with portfolios, rather than individual securities. Since expected returns and market betas combine in the same way in portfolios, if the CAPM explains security returns it also explains portfolio returns.[4] Estimates of beta for diversified portfolios are more precise than estimates for individual securities. Thus, using portfolios in cross-section regressions of average returns on betas reduces the critical errors in variables problem. Grouping, however, shrinks the range of betas and reduces statistical power. To mitigate this problem, researchers sort securities on beta when forming portfolios; the first portfolio contains securities with the lowest betas, and so on, up to the last portfolio with the highest beta assets. This sorting procedure is now standard in empirical tests.

Fama and MacBeth (1973) propose a method for addressing the inference problem caused by correlation of the residuals in cross-section regressions. Instead of estimating a single cross-section regression of average monthly returns on betas, they estimate month-by-month cross-section regressions of monthly returns on betas. The times-series means of the monthly slopes and intercepts, along with the standard errors of the means, are then used to test whether the average premium for beta is positive and whether the average return on assets uncorrelated with the market is equal to the average risk-free interest rate. In this approach, the standard errors of the average intercept and slope are determined by the month-to-month variation in the regression coefficients, which fully captures the effects of residual correlation on variation in the regression coefficients, but sidesteps the problem of actually estimating the correlations. The residual correlations are, in effect, captured via repeated sampling of the regression coefficients. This approach also becomes standard in the literature.

Jensen (1968) was the first to note that the Sharpe-Lintner version of the

[4] Formally, if x_{ip}, $i = 1, \ldots, N$, are the weights for assets in some portfolio p, the expected return and market beta for the portfolio are related to the expected returns and betas of assets as

$$E(R_p) = \sum_{i=1}^{N} x_{ip}E(R_i), \text{ and } \beta_{pM} = \sum_{i=1}^{N} x_{ip}\beta_{pM}.$$

Thus, the CAPM relation between expected return and beta,

$$E(R_i) = E(R_f) + [E(R_M) - E(R_f)]\beta_{iM},$$

holds when asset i is a portfolio, as well as when i is an individual security.

relation between expected return and market beta also implies a time-series regression test. The Sharpe-Lintner CAPM says that the expected value of an asset's excess return (the asset's return minus the risk-free interest rate, $R_{it} - R_{ft}$) is completely explained by its expected CAPM risk premium (its beta times the expected value of $R_{Mt} - R_{ft}$). This implies that "Jensen's alpha," the intercept term in the time-series regression,

$$\text{(Time-Series Regression)} \quad R_{it} - R_{ft} = \alpha_i + \beta_{iM}(R_{Mt} - R_{ft}) + \varepsilon_{it},$$

is zero for each asset.

The early tests firmly reject the Sharpe-Lintner version of the CAPM. There is a positive relation between beta and average return, but it is too "flat." Recall that, in cross-section regressions, the Sharpe-Lintner model predicts that the intercept is the risk-free rate and the coefficient on beta is the expected market return in excess of the risk-free rate, $E(R_M) - R_f$. The regressions consistently find that the intercept is greater than the average risk-free rate (typically proxied as the return on a one-month Treasury bill), and the coefficient on beta is less than the average excess market return (proxied as the average return on a portfolio of U.S. common stocks minus the Treasury bill rate). This is true in the early tests, such as Douglas (1968), Black, Jensen and Scholes (1972), Miller and Scholes (1972), Blume and Friend (1973) and Fama and MacBeth (1973), as well as in more recent cross-section regression tests, like Fama and French (1992).

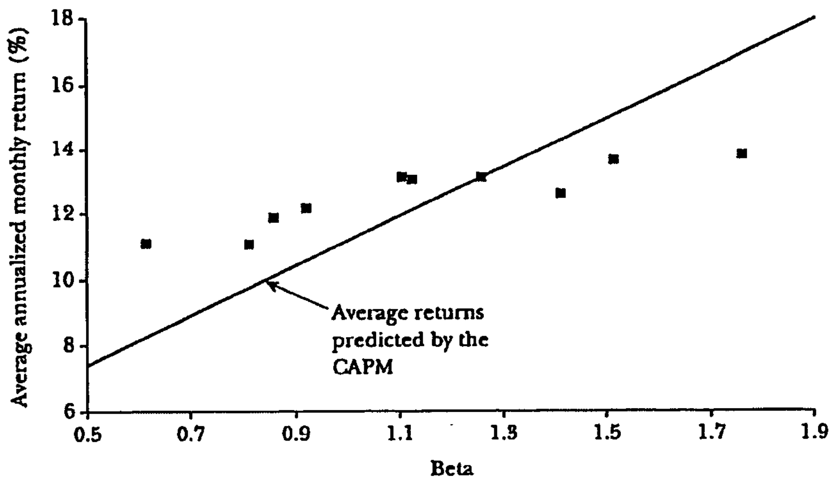
The evidence that the relation between beta and average return is too flat is confirmed in time-series tests, such as Friend and Blume (1970), Black, Jensen and Scholes (1972) and Stambaugh (1982). The intercepts in time-series regressions of excess asset returns on the excess market return are positive for assets with low betas and negative for assets with high betas.

Figure 2 provides an updated example of the evidence. In December of each year, we estimate a preranking beta for every NYSE (1928–2003), AMEX (1963–2003) and NASDAQ (1972–2003) stock in the CRSP (Center for Research in Security Prices of the University of Chicago) database, using two to five years (as available) of prior monthly returns.[5] We then form ten value-weight portfolios based on these preranking betas and compute their returns for the next twelve months. We repeat this process for each year from 1928 to 2003. The result is 912 monthly returns on ten beta-sorted portfolios. Figure 2 plots each portfolio's average return against its postranking beta, estimated by regressing its monthly returns for 1928–2003 on the return on the CRSP value-weight portfolio of U.S. common stocks.

The Sharpe-Lintner CAPM predicts that the portfolios plot along a straight

[5] To be included in the sample for year t, a security must have market equity data (price times shares outstanding) for December of $t - 1$, and CRSP must classify it as ordinary common equity. Thus, we exclude securities such as American Depository Receipts (ADRs) and Real Estate Investment Trusts (REITs).

Figure 2
Average Annualized Monthly Return versus Beta for Value Weight Portfolios Formed on Prior Beta, 1928–2003



line, with an intercept equal to the risk-free rate, R_f, and a slope equal to the expected excess return on the market, $E(R_M) - R_f$. We use the average one-month Treasury bill rate and the average excess CRSP market return for 1928–2003 to estimate the predicted line in Figure 2. Confirming earlier evidence, the relation between beta and average return for the ten portfolios is much flatter than the Sharpe-Lintner CAPM predicts. The returns on the low beta portfolios are too high, and the returns on the high beta portfolios are too low. For example, the predicted return on the portfolio with the lowest beta is 8.3 percent per year; the actual return is 11.1 percent. The predicted return on the portfolio with the highest beta is 16.8 percent per year; the actual is 13.7 percent.

Although the observed premium per unit of beta is lower than the Sharpe-Lintner model predicts, the relation between average return and beta in Figure 2 is roughly linear. This is consistent with the Black version of the CAPM, which predicts only that the beta premium is positive. Even this less restrictive model, however, eventually succumbs to the data.

Testing Whether Market Betas Explain Expected Returns

The Sharpe-Lintner and Black versions of the CAPM share the prediction that the market portfolio is mean-variance-efficient. This implies that differences in expected return across securities and portfolios are entirely explained by differences in market beta; other variables should add nothing to the explanation of expected return. This prediction plays a prominent role in tests of the CAPM. In the early work, the weapon of choice is cross-section regressions.

In the framework of Fama and MacBeth (1973), one simply adds predetermined explanatory variables to the month-by-month cross-section regressions of returns on beta. If all differences in expected return are explained by beta, the average slopes on the additional variables should not be reliably different from zero. Clearly, the trick in the cross-section regression approach is to choose specific additional variables likely to expose any problems of the CAPM prediction that, because the market portfolio is efficient, market betas suffice to explain expected asset returns.

For example, in Fama and MacBeth (1973) the additional variables are squared market betas (to test the prediction that the relation between expected return and beta is linear) and residual variances from regressions of returns on the market return (to test the prediction that market beta is the only measure of risk needed to explain expected returns). These variables do not add to the explanation of average returns provided by beta. Thus, the results of Fama and MacBeth (1973) are consistent with the hypothesis that their market proxy—an equal-weight portfolio of NYSE stocks—is on the minimum variance frontier.

The hypothesis that market betas completely explain expected returns can also be tested using time-series regressions. In the time-series regression described above (the excess return on asset i regressed on the excess market return), the intercept is the difference between the asset's average excess return and the excess return predicted by the Sharpe-Lintner model, that is, beta times the average excess market return. If the model holds, there is no way to group assets into portfolios whose intercepts are reliably different from zero. For example, the intercepts for a portfolio of stocks with high ratios of earnings to price and a portfolio of stocks with low earning-price ratios should both be zero. Thus, to test the hypothesis that market betas suffice to explain expected returns, one estimates the time-series regression for a set of assets (or portfolios) and then jointly tests the vector of regression intercepts against zero. The trick in this approach is to choose the left-hand-side assets (or portfolios) in a way likely to expose any shortcoming of the CAPM prediction that market betas suffice to explain expected asset returns.

In early applications, researchers use a variety of tests to determine whether the intercepts in a set of time-series regressions are all zero. The tests have the same asymptotic properties, but there is controversy about which has the best small sample properties. Gibbons, Ross and Shanken (1989) settle the debate by providing an F-test on the intercepts that has exact small-sample properties. They also show that the test has a simple economic interpretation. In effect, the test constructs a candidate for the tangency portfolio T in Figure 1 by optimally combining the market proxy and the left-hand-side assets of the time-series regressions. The estimator then tests whether the efficient set provided by the combination of this tangency portfolio and the risk-free asset is reliably superior to the one obtained by combining the risk-free asset with the market proxy alone. In other words, the Gibbons, Ross and Shanken statistic tests whether the market proxy is the tangency portfolio in the set of portfolios that can be constructed by combining the market portfolio with the specific assets used as dependent variables in the time-series regressions.

Enlightened by this insight of Gibbons, Ross and Shanken (1989), one can see a similar interpretation of the cross-section regression test of whether market betas suffice to explain expected returns. In this case, the test is whether the additional explanatory variables in a cross-section regression identify patterns in the returns on the left-hand-side assets that are not explained by the assets' market betas. This amounts to testing whether the market proxy is on the minimum variance frontier that can be constructed using the market proxy and the left-hand-side assets included in the tests.

An important lesson from this discussion is that time-series and cross-section regressions do not, strictly speaking, test the CAPM. What is literally tested is whether a specific proxy for the market portfolio (typically a portfolio of U.S. common stocks) is efficient in the set of portfolios that can be constructed from it and the left-hand-side assets used in the test. One might conclude from this that the CAPM has never been tested, and prospects for testing it are not good because 1) the set of left-hand-side assets does not include all marketable assets, and 2) data for the true market portfolio of all assets are likely beyond reach (Roll, 1977; more on this later). But this criticism can be leveled at tests of any economic model when the tests are less than exhaustive or when they use proxies for the variables called for by the model.

The bottom line from the early cross-section regression tests of the CAPM, such as Fama and MacBeth (1973), and the early time-series regression tests, like Gibbons (1982) and Stambaugh (1982), is that standard market proxies seem to be on the minimum variance frontier. That is, the central predictions of the Black version of the CAPM, that market betas suffice to explain expected returns and that the risk premium for beta is positive, seem to hold. But the more specific prediction of the Sharpe-Lintner CAPM that the premium per unit of beta is the expected market return minus the risk-free interest rate is consistently rejected.

The success of the Black version of the CAPM in early tests produced a consensus that the model is a good description of expected returns. These early results, coupled with the model's simplicity and intuitive appeal, pushed the CAPM to the forefront of finance.

Recent Tests

Starting in the late 1970s, empirical work appears that challenges even the Black version of the CAPM. Specifically, evidence mounts that much of the variation in expected return is unrelated to market beta.

The first blow is Basu's (1977) evidence that when common stocks are sorted on earnings-price ratios, future returns on high E/P stocks are higher than predicted by the CAPM. Banz (1981) documents a size effect: when stocks are sorted on market capitalization (price times shares outstanding), average returns on small stocks are higher than predicted by the CAPM. Bhandari (1988) finds that high debt-equity ratios (book value of debt over the market value of equity, a measure of leverage) are associated with returns that are too high relative to their market betas.

Finally, Statman (1980) and Rosenberg, Reid and Lanstein (1985) document that stocks with high book-to-market equity ratios (B/M, the ratio of the book value of a common stock to its market value) have high average returns that are not captured by their betas.

There is a theme in the contradictions of the CAPM summarized above. Ratios involving stock prices have information about expected returns missed by market betas. On reflection, this is not surprising. A stock's price depends not only on the expected cash flows it will provide, but also on the expected returns that discount expected cash flows back to the present. Thus, in principle, the cross-section of prices has information about the cross-section of expected returns. (A high expected return implies a high discount rate and a low price.) The cross-section of stock prices is, however, arbitrarily affected by differences in scale (or units). But with a judicious choice of scaling variable X, the ratio X/P can reveal differences in the cross-section of expected stock returns. Such ratios are thus prime candidates to expose shortcomings of asset pricing models—in the case of the CAPM, shortcomings of the prediction that market betas suffice to explain expected returns (Ball, 1978). The contradictions of the CAPM summarized above suggest that earnings-price, debt-equity and book-to-market ratios indeed play this role.

Fama and French (1992) update and synthesize the evidence on the empirical failures of the CAPM. Using the cross-section regression approach, they confirm that size, earnings-price, debt-equity and book-to-market ratios add to the explanation of expected stock returns provided by market beta. Fama and French (1996) reach the same conclusion using the time-series regression approach applied to portfolios of stocks sorted on price ratios. They also find that different price ratios have much the same information about expected returns. This is not surprising given that price is the common driving force in the price ratios, and the numerators are just scaling variables used to extract the information in price about expected returns.

Fama and French (1992) also confirm the evidence (Reinganum, 1981; Stambaugh, 1982; Lakonishok and Shapiro, 1986) that the relation between average return and beta for common stocks is even flatter after the sample periods used in the early empirical work on the CAPM. The estimate of the beta premium is, however, clouded by statistical uncertainty (a large standard error). Kothari, Shanken and Sloan (1995) try to resuscitate the Sharpe-Lintner CAPM by arguing that the weak relation between average return and beta is just a chance result. But the strong evidence that other variables capture variation in expected return missed by beta makes this argument irrelevant. If betas do not suffice to explain expected returns, the market portfolio is not efficient, and the CAPM is dead in its tracks. Evidence on the size of the market premium can neither save the model nor further doom it.

The synthesis of the evidence on the empirical problems of the CAPM provided by Fama and French (1992) serves as a catalyst, marking the point when it is generally acknowledged that the CAPM has potentially fatal problems. Research then turns to explanations.

One possibility is that the CAPM's problems are spurious, the result of data dredging—publication-hungry researchers scouring the data and unearthing contradictions that occur in specific samples as a result of chance. A standard response to this concern is to test for similar findings in other samples. Chan, Hamao and Lakonishok (1991) find a strong relation between book-to-market equity (B/M) and average return for Japanese stocks. Capaul, Rowley and Sharpe (1993) observe a similar B/M effect in four European stock markets and in Japan. Fama and French (1998) find that the price ratios that produce problems for the CAPM in U.S. data show up in the same way in the stock returns of twelve non-U.S. major markets, and they are present in emerging market returns. This evidence suggests that the contradictions of the CAPM associated with price ratios are not sample specific.

Explanations: Irrational Pricing or Risk

Among those who conclude that the empirical failures of the CAPM are fatal, two stories emerge. On one side are the behavioralists. Their view is based on evidence that stocks with high ratios of book value to market price are typically firms that have fallen on bad times, while low B/M is associated with growth firms (Lakonishok, Shleifer and Vishny, 1994; Fama and French, 1995). The behavioralists argue that sorting firms on book-to-market ratios exposes investor overreaction to good and bad times. Investors overextrapolate past performance, resulting in stock prices that are too high for growth (low B/M) firms and too low for distressed (high B/M, so-called value) firms. When the overreaction is eventually corrected, the result is high returns for value stocks and low returns for growth stocks. Proponents of this view include DeBondt and Thaler (1987), Lakonishok, Shleifer and Vishny (1994) and Haugen (1995).

The second story for explaining the empirical contradictions of the CAPM is that they point to the need for a more complicated asset pricing model. The CAPM is based on many unrealistic assumptions. For example, the assumption that investors care only about the mean and variance of one-period portfolio returns is extreme. It is reasonable that investors also care about how their portfolio return covaries with labor income and future investment opportunities, so a portfolio's return variance misses important dimensions of risk. If so, market beta is not a complete description of an asset's risk, and we should not be surprised to find that differences in expected return are not completely explained by differences in beta. In this view, the search should turn to asset pricing models that do a better job explaining average returns.

Merton's (1973) intertemporal capital asset pricing model (ICAPM) is a natural extension of the CAPM. The ICAPM begins with a different assumption about investor objectives. In the CAPM, investors care only about the wealth their portfolio produces at the end of the current period. In the ICAPM, investors are concerned not only with their end-of-period payoff, but also with the opportunities they will have to consume or invest the payoff. Thus, when choosing a portfolio at time $t-1$, ICAPM investors consider how their wealth at t might vary with future *state variables*, including labor income, the prices of consumption goods and the nature of portfolio opportunities at t, and expectations about the labor income, consumption and investment opportunities to be available after t.

Like CAPM investors, ICAPM investors prefer high expected return and low return variance. But ICAPM investors are also concerned with the covariances of portfolio returns with state variables. As a result, optimal portfolios are "multifactor efficient," which means they have the largest possible expected returns, given their return variances and the covariances of their returns with the relevant state variables.

Fama (1996) shows that the ICAPM generalizes the logic of the CAPM. That is, if there is risk-free borrowing and lending or if short sales of risky assets are allowed, market clearing prices imply that the market portfolio is multifactor efficient. Moreover, multifactor efficiency implies a relation between expected return and beta risks, but it requires additional betas, along with a market beta, to explain expected returns.

An ideal implementation of the ICAPM would specify the state variables that affect expected returns. Fama and French (1993) take a more indirect approach, perhaps more in the spirit of Ross's (1976) arbitrage pricing theory. They argue that though size and book-to-market equity are not themselves state variables, the higher average returns on small stocks and high book-to-market stocks reflect unidentified state variables that produce undiversifiable risks (covariances) in returns that are not captured by the market return and are priced separately from market betas. In support of this claim, they show that the returns on the stocks of small firms covary more with one another than with returns on the stocks of large firms, and returns on high book-to-market (value) stocks covary more with one another than with returns on low book-to-market (growth) stocks. Fama and French (1995) show that there are similar size and book-to-market patterns in the covariation of fundamentals like earnings and sales.

Based on this evidence, Fama and French (1993, 1996) propose a three-factor model for expected returns,

$$\text{(Three-Factor Model)} \quad E(R_{it}) - R_{ft} = \beta_{iM}[E(R_{Mt}) - R_{ft}] + \beta_{is}E(SMB_t) + \beta_{ih}E(HML_t).$$

In this equation, SMB_t (small minus big) is the difference between the returns on diversified portfolios of small and big stocks, HML_t (high minus low) is the difference between the returns on diversified portfolios of high and low B/M stocks, and the betas are slopes in the multiple regression of $R_{it} - R_{ft}$ on $R_{Mt} - R_{ft}$, SMB_t and HML_t.

For perspective, the average value of the market premium $R_{Mt} - R_{ft}$ for 1927–2003 is 8.3 percent per year, which is 3.5 standard errors from zero. The average values of SMB_t, and HML_t are 3.6 percent and 5.0 percent per year, and they are 2.1 and 3.1 standard errors from zero. All three premiums are volatile, with annual standard deviations of 21.0 percent ($R_{Mt} - R_{ft}$), 14.6 percent (SMB_t) and 14.2 percent (HML_t) per year. Although the average values of the premiums are large, high volatility implies substantial uncertainty about the true expected premiums.

One implication of the expected return equation of the three-factor model is that the intercept α_i in the time-series regression,

$$R_{it} - R_{ft} = \alpha_i + \beta_{iM}(R_{Mt} - R_{ft}) + \beta_{is}SMB_t + \beta_{ih}HML_t + \varepsilon_{it},$$

is zero for all assets *i*. Using this criterion, Fama and French (1993, 1996) find that the model captures much of the variation in average return for portfolios formed on size, book-to-market equity and other price ratios that cause problems for the CAPM. Fama and French (1998) show that an international version of the model performs better than an international CAPM in describing average returns on portfolios formed on scaled price variables for stocks in 13 major markets.

The three-factor model is now widely used in empirical research that requires a model of expected returns. Estimates of α_i from the time-series regression above are used to calibrate how rapidly stock prices respond to new information (for example, Loughran and Ritter, 1995; Mitchell and Stafford, 2000). They are also used to measure the special information of portfolio managers, for example, in Carhart's (1997) study of mutual fund performance. Among practitioners like Ibbotson Associates, the model is offered as an alternative to the CAPM for estimating the cost of equity capital.

From a theoretical perspective, the main shortcoming of the three-factor model is its empirical motivation. The small-minus-big (SMB) and high-minus-low (HML) explanatory returns are not motivated by predictions about state variables of concern to investors. Instead they are brute force constructs meant to capture the patterns uncovered by previous work on how average stock returns vary with size and the book-to-market equity ratio.

But this concern is not fatal. The ICAPM does not require that the additional portfolios used along with the market portfolio to explain expected returns "mimic" the relevant state variables. In both the ICAPM and the arbitrage pricing theory, it suffices that the additional portfolios are well diversified (in the terminology of Fama, 1996, they are multifactor minimum variance) and that they are sufficiently different from the market portfolio to capture covariation in returns and variation in expected returns missed by the market portfolio. Thus, adding diversified portfolios that capture covariation in returns and variation in average returns left unexplained by the market is in the spirit of both the ICAPM and the Ross's arbitrage pricing theory.

The behavioralists are not impressed by the evidence for a risk-based explanation of the failures of the CAPM. They typically concede that the three-factor model captures covariation in returns missed by the market return and that it picks up much of the size and value effects in average returns left unexplained by the CAPM. But their view is that the average return premium associated with the model's book-to-market factor—which does the heavy lifting in the improvements to the CAPM—is itself the result of investor overreaction that happens to be correlated across firms in a way that just looks like a risk story. In short, in the behavioral view, the market tries to set CAPM prices, and violations of the CAPM are due to mispricing.

The conflict between the behavioral irrational pricing story and the rational risk story for the empirical failures of the CAPM leaves us at a timeworn impasse. Fama (1970) emphasizes that the hypothesis that prices properly reflect available information must be tested in the context of a model of expected returns, like the CAPM. Intuitively, to test whether prices are rational, one must take a stand on what the market is trying to do in setting prices—that is, what is risk and what is the relation between expected return and risk? When tests reject the CAPM, one cannot say whether the problem is its assumption that prices are rational (the behavioral view) or violations of other assumptions that are also necessary to produce the CAPM (our position).

Fortunately, for some applications, the way one uses the three-factor model does not depend on one's view about whether its average return premiums are the rational result of underlying state variable risks, the result of irrational investor behavior or sample specific results of chance. For example, when measuring the response of stock prices to new information or when evaluating the performance of managed portfolios, one wants to account for known patterns in returns and average returns for the period examined, whatever their source. Similarly, when estimating the cost of equity capital, one might be unconcerned with whether expected return premiums are rational or irrational since they are in either case part of the opportunity cost of equity capital (Stein, 1996). But the cost of capital is forward looking, so if the premiums are sample specific they are irrelevant.

The three-factor model is hardly a panacea. Its most serious problem is the momentum effect of Jegadeesh and Titman (1993). Stocks that do well relative to the market over the last three to twelve months tend to continue to do well for the next few months, and stocks that do poorly continue to do poorly. This momentum effect is distinct from the value effect captured by book-to-market equity and other price ratios. Moreover, the momentum effect is left unexplained by the three-factor model, as well as by the CAPM. Following Carhart (1997), one response is to add a momentum factor (the difference between the returns on diversified portfolios of short-term winners and losers) to the three-factor model. This step is again legitimate in applications where the goal is to abstract from known patterns in average returns to uncover information-specific or manager-specific effects. But since the momentum effect is short-lived, it is largely irrelevant for estimates of the cost of equity capital.

Another strand of research points to problems in both the three-factor model and the CAPM. Frankel and Lee (1998), Dechow, Hutton and Sloan (1999), Piotroski (2000) and others show that in portfolios formed on price ratios like book-to-market equity, stocks with higher expected cash flows have higher average returns that are not captured by the three-factor model or the CAPM. The authors interpret their results as evidence that stock prices are irrational, in the sense that they do not reflect available information about expected profitability.

In truth, however, one can't tell whether the problem is bad pricing or a bad asset pricing model. A stock's price can always be expressed as the present value of expected future cash flows discounted at the expected return on the stock (Campbell and Shiller, 1989; Vuolteenaho, 2002). It follows that if two stocks have the same price, the one with higher expected cash flows must have a higher expected return. This holds true whether pricing is rational or irrational. Thus, when one observes a positive relation between expected cash flows and expected returns that is left unexplained by the CAPM or the three-factor model, one can't tell whether it is the result of irrational pricing or a misspecified asset pricing model.

The Market Proxy Problem

Roll (1977) argues that the CAPM has never been tested and probably never will be. The problem is that the market portfolio at the heart of the model is theoretically and empirically elusive. It is not theoretically clear which assets (for example, human capital) can legitimately be excluded from the market portfolio, and data availability substantially limits the assets that are included. As a result, tests of the CAPM are forced to use proxies for the market portfolio, in effect testing whether the proxies are on the minimum variance frontier. Roll argues that because the tests use proxies, not the true market portfolio, we learn nothing about the CAPM.

We are more pragmatic. The relation between expected return and market beta of the CAPM is just the minimum variance condition that holds in any efficient portfolio, applied to the market portfolio. Thus, if we can find a market proxy that is on the minimum variance frontier, it can be used to describe differences in expected returns, and we would be happy to use it for this purpose. The strong rejections of the CAPM described above, however, say that researchers have not uncovered a reasonable market proxy that is close to the minimum variance frontier. If researchers are constrained to reasonable proxies, we doubt they ever will.

Our pessimism is fueled by several empirical results. Stambaugh (1982) tests the CAPM using a range of market portfolios that include, in addition to U.S. common stocks, corporate and government bonds, preferred stocks, real estate and other consumer durables. He finds that tests of the CAPM are not sensitive to expanding the market proxy beyond common stocks, basically because the volatility of expanded market returns is dominated by the volatility of stock returns.

One need not be convinced by Stambaugh's (1982) results since his market proxies are limited to U.S. assets. If international capital markets are open and asset prices conform to an international version of the CAPM, the market portfolio should include international assets. Fama and French (1998) find, however, that betas for a global stock market portfolio cannot explain the high average returns observed around the world on stocks with high book-to-market or high earnings-price ratios.

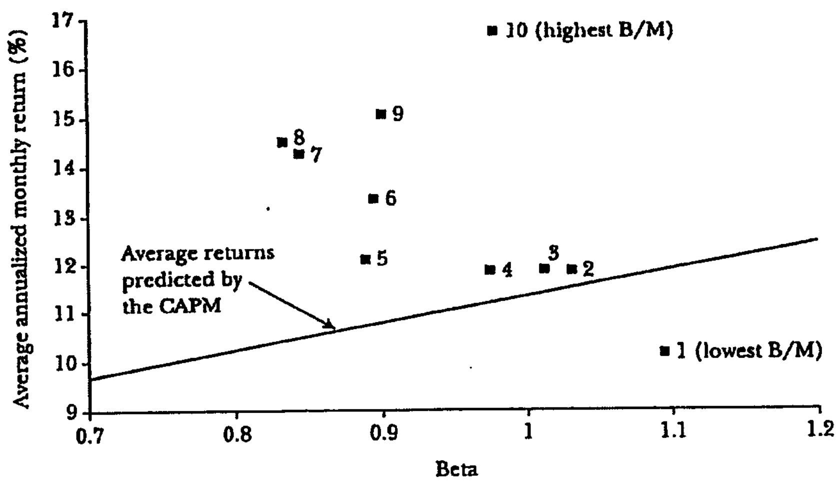
A major problem for the CAPM is that portfolios formed by sorting stocks on price ratios produce a wide range of average returns, but the average returns are not positively related to market betas (Lakonishok, Shleifer and Vishny, 1994; Fama and French, 1996, 1998). The problem is illustrated in Figure 3, which shows average returns and betas (calculated with respect to the CRSP value-weight portfolio of NYSE, AMEX and NASDAQ stocks) for July 1963 to December 2003 for ten portfolios of U.S. stocks formed annually on sorted values of the book-to-market equity ratio (B/M).[6]

Average returns on the B/M portfolios increase almost monotonically, from 10.1 percent per year for the lowest B/M group (portfolio 1) to an impressive 16.7 percent for the highest (portfolio 10). But the positive relation between beta and average return predicted by the CAPM is notably absent. For example, the portfolio with the lowest book-to-market ratio has the highest beta but the lowest average return. The estimated beta for the portfolio with the highest book-to-market ratio and the highest average return is only 0.98. With an average annualized value of the riskfree interest rate, R_f, of 5.8 percent and an average annualized market premium, $R_M - R_f$, of 11.3 percent, the Sharpe-Lintner CAPM predicts an average return of 11.8 percent for the lowest B/M portfolio and 11.2 percent for the highest, far from the observed values, 10.1 and 16.7 percent. For the Sharpe-Lintner model to "work" on these portfolios, their market betas must change dramatically, from 1.09 to 0.78 for the lowest B/M portfolio and from 0.98 to 1.98 for the highest. We judge it unlikely that alternative proxies for the market portfolio will produce betas and a market premium that can explain the average returns on these portfolios.

It is always possible that researchers will redeem the CAPM by finding a reasonable proxy for the market portfolio that is on the minimum variance frontier. We emphasize, however, that this possibility cannot be used to justify the way the CAPM is currently applied. The problem is that applications typically use the same

[6] Stock return data are from CRSP, and book equity data are from Compustat and the Moody's Industrials, Transportation, Utilities and Financials manuals. Stocks are allocated to ten portfolios at the end of June of each year t (1963 to 2003) using the ratio of book equity for the fiscal year ending in calendar year $t - 1$, divided by market equity at the end of December of $t - 1$. Book equity is the book value of stockholders' equity, plus balance sheet deferred taxes and investment tax credit (if available), minus the book value of preferred stock. Depending on availability, we use the redemption, liquidation or par value (in that order) to estimate the book value of preferred stock. Stockholders' equity is the value reported by Moody's or Compustat, if it is available. If not, we measure stockholders' equity as the book value of common equity plus the par value of preferred stock or the book value of assets minus total liabilities (in that order). The portfolios for year t include NYSE (1963–2003), AMEX (1963–2003) and NASDAQ (1972–2003) stocks with positive book equity in $t - 1$ and market equity (from CRSP) for December of $t - 1$ and June of t. The portfolios exclude securities CRSP does not classify as ordinary common equity. The breakpoints for year t use only securities that are on the NYSE in June of year t.

Figure 3
Average Annualized Monthly Return versus Beta for Value Weight Portfolios Formed on B/M, 1963–2003



market proxies, like the value-weight portfolio of U.S. stocks, that lead to rejections of the model in empirical tests. The contradictions of the CAPM observed when such proxies are used in tests of the model show up as bad estimates of expected returns in applications; for example, estimates of the cost of equity capital that are too low (relative to historical average returns) for small stocks and for stocks with high book-to-market equity ratios. In short, if a market proxy does not work in tests of the CAPM, it does not work in applications.

Conclusions

The version of the CAPM developed by Sharpe (1964) and Lintner (1965) has never been an empirical success. In the early empirical work, the Black (1972) version of the model, which can accommodate a flatter tradeoff of average return for market beta, has some success. But in the late 1970s, research begins to uncover variables like size, various price ratios and momentum that add to the explanation of average returns provided by beta. The problems are serious enough to invalidate most applications of the CAPM.

For example, finance textbooks often recommend using the Sharpe-Lintner CAPM risk-return relation to estimate the cost of equity capital. The prescription is to estimate a stock's market beta and combine it with the risk-free interest rate and the average market risk premium to produce an estimate of the cost of equity. The typical market portfolio in these exercises includes just U.S. common stocks. But empirical work, old and new, tells us that the relation between beta and average return is flatter than predicted by the Sharpe-Lintner version of the CAPM. As a result, CAPM estimates of the cost of equity for high beta stocks are too high (relative to historical average returns) and estimates for low beta stocks are too low (Friend and Blume, 1970). Similarly, if the high average returns on value stocks (with high book-to-market ratios) imply high expected returns, CAPM cost of equity estimates for such stocks are too low.[7]

The CAPM is also often used to measure the performance of mutual funds and other managed portfolios. The approach, dating to Jensen (1968), is to estimate the CAPM time-series regression for a portfolio and use the intercept (Jensen's alpha) to measure abnormal performance. The problem is that, because of the empirical failings of the CAPM, even passively managed stock portfolios produce abnormal returns if their investment strategies involve tilts toward CAPM problems (Elton, Gruber, Das and Hlavka, 1993). For example, funds that concentrate on low beta stocks, small stocks or value stocks will tend to produce positive abnormal returns relative to the predictions of the Sharpe-Lintner CAPM, even when the fund managers have no special talent for picking winners.

The CAPM, like Markowitz's (1952, 1959) portfolio model on which it is built, is nevertheless a theoretical tour de force. We continue to teach the CAPM as an introduction to the fundamental concepts of portfolio theory and asset pricing, to be built on by more complicated models like Merton's (1973) ICAPM. But we also warn students that despite its seductive simplicity, the CAPM's empirical problems probably invalidate its use in applications.

■ *We gratefully acknowledge the comments of John Cochrane, George Constantinides, Richard Leftwich, Andrei Shleifer, René Stulz and Timothy Taylor.*

[7] The problems are compounded by the large standard errors of estimates of the market premium and of betas for individual stocks, which probably suffice to make CAPM estimates of the cost of equity rather meaningless, even if the CAPM holds (Fama and French, 1997; Pastor and Stambaugh, 1999). For example, using the U.S. Treasury bill rate as the risk-free interest rate and the CRSP value-weight portfolio of publicly traded U.S. common stocks, the average value of the equity premium $R_{Mt} - R_{ft}$ for 1927–2003 is 8.3 percent per year, with a standard error of 2.4 percent. The two standard error range thus runs from 3.5 percent to 13.1 percent, which is sufficient to make most projects appear either profitable or unprofitable. This problem is, however, hardly special to the CAPM. For example, expected returns in all versions of Merton's (1973) ICAPM include a market beta and the expected market premium. Also, as noted earlier the expected values of the size and book-to-market premiums in the Fama-French three-factor model are also estimated with substantial error.

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Comparable Earnings: New Life for an Old Precept

by
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Comparable Earnings: New Life for an Old Precept

Accelerating deregulation has greatly increased the investment risk of natural gas utilities. As a result, the authors believe it more appropriate than ever to employ the comparable earnings model. We believe our application of the model overcomes the greatest traditional objection to it — lack of comparability of the selected non-utility proxy firms. Our illustration focuses on a target gas pipeline company with a beta of 0.96 — almost equal to the market's beta of 1.00


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Introduction

The comparable earnings model used to determine a common equity cost rate is deeply rooted in the standard of "corresponding risk" enunciated in the landmark *Bluefield* and *Hope* decisions of the U.S. Supreme Court.[1] With such solid grounding in the foundations of rate of return regulation, comparable earnings should be accepted as a principal model, along with the currently popular market-based models, provided that its most common criticism, non-comparability of the proxy companies, is overcome.

Our comparable earnings model overcomes the non-comparability issue of the non-utility firms selected as a proxy for the target utility, in this example, a gas pipeline company. We should note that in the absence of common stock prices for the target utility (as with a wholly-owned subsidiary), it is appropriate to use the average of a proxy group of similar risk gas pipeline companies whose common stocks are actively traded. As we will demonstrate, our selection process results in a group of domestic, non-utility firms that is comparable in total risk, the sum of business and financial risk, which reflects both non-diversifiable systematic, or market, risk as well as diversifiable unsystematic, or firm-specific, risk.

Embedded in the Landmark Decisions

As stated in *Bluefield* in 1922: "A public utility is entitled to such rates as will permit it to earn a return . . on investments in other business undertakings which are attended by corresponding risks and uncertainties ..."

In addition, the court stated in *Hope* in 1944: "By that standard the return to the equity owner should be commensurate with returns on investments in other enterprises having corresponding risks"

Thus, the "corresponding risk" precept of *Bluefield* and *Hope* predates the use of such market-based cost-of-equity models as the Discounted Cash Flow (DCF) and Capital Asset Pricing (CAPM), which were developed later and are currently popular in rate-base/rate-of-return regulation. Consequently, the comparable earnings model has a longer regulatory and judicial history. However, it has far greater relevance now than ever before in its history because significant deregulation has substantially increased natural gas utilities' investment risk to a level similar to that of non-utility firms. As a result, it is

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more important than ever to look to similar-risk non-utility firms for insight into common equity cost rate, especially in view of the deficiencies inherent in the currently popular market-based cost of common equity models, particularly the DCF model

Despite the fact that the landmark decisions are still regarded as having set the standards for determining a fair rate of return, the comparable earnings model has experienced decreased usage by expert witnesses, as well as less regulatory acceptance over the years. We believe the decline in the popularity of the comparable earnings model, in large measure, is attributable to the difficulty of selecting non-utility proxy firms that regulators will accept as comparable to the target utility. Regulatory acceptance is difficult to gain when the selection process is arbitrary. Our application of the model is objective and consistent with fundamental financial tenets.

Principles of Comparable Earnings

Regulation is a substitute for the competition of the marketplace. Moreover, regulated public utilities compete in the capital markets with all firms, including unregulated non-utilities. The comparable earnings model is based upon the opportunity cost principle; i.e., that the true cost of an investment is the return that could have been earned on the next best available alternative investment of similar risk. Consequently, the comparable earnings model is consistent with regulatory and financial principles, as it is a surrogate for the competition of the marketplace, and investors seek the greatest available rate of return for bearing similar risk.

The selection of comparable firms is the most difficult step in applying the comparable earnings model, as noted by Phillips[2] as well as by Bonbright, Danielsen and Kamerschen.[3] The selection of non-utility proxy firms should result in a sufficiently broad-based group in order to minimize the effect of company-specific aberrations. However, if the selection process is arbitrary, it likely would result in a proxy group that is too broad-based, such as the Standard & Poor's 500 Composite Index or the Value Line Industrial Composite. The use of such groups would require subjective adjustments to the comparable earnings results to reflect risk differences between the group(s) and the target utility, a gas pipeline company in this example.

Authors' Selection Criteria

We base the selection of comparable non-utility firms on market-based, objective, quantitative measures of risk resulting from market prices that subsume investors' assessments of all elements of risk. Thus, our approach is based upon the principle of risk and return; namely, that firms of comparable risk should be expected to earn comparable returns. It is also consistent with the "corresponding risk" standard established in *Bluefield* and *Hope*. We measure total investment risk as the sum of non-diversifiable systematic and diversifiable unsystematic risk. We use the unadjusted beta as a measure of systematic risk and the standard error of the estimate (residual standard error) as a measure of unsystematic risk. Both the unadjusted beta and the residual standard error are derived from a regression of the target utility's security returns relative to the market's returns, which takes the general form:

$$r_{it} = a_i + b_i r_{mt} + e_{it}$$

where:

r_{it} = tth observation of the ith utility's rate of return
r_{mt} = tth observation of the market's rate of return
e_{it} = tth random error term
a_i = constant least-squares regression coefficient
b_i = least-squares regression slope coefficient, the unadjusted beta.

As shown by Francis,[4] the total variation or risk of a firm's return, Var (r_i), comes from two sources:

Var (r_i) = total risk of ith asset
= $\mathrm{var}(a_i + b_i r_m + e)$ substituting $(a_i + b_i r_m + e)$ for r_i
= $\mathrm{var}(b_i r_m)$ + var (e) since $\mathrm{var}(a_i) = 0$
= $b_i^2\,\mathrm{var}(r_m)$ + var (e) since $\mathrm{var}(b_i r_m) = b_i^2\,\mathrm{var}(r_m)$
= systematic + unsystematic risk

Francis[5] also notes: "The term $\sigma^2(r_i|r_m)$ is called the *residual variance around the regression line* in statistical terms or *unsystematic risk* in capital market theory language. $\sigma^2(r_i|r_m) = \ldots = \mathrm{var}(e)$. The residual variance is the squared standard error in regression language, a measure of unsystematic risk." Application of these criteria results in a group of non-utility firms whose average total investment risk is indeed comparable to that of the target gas pipeline.

As a measure of systematic risk, we use the Value Line unadjusted beta. Beta measures the extent to which market-wide or macro-economic events affect a firm's stock price. We use the unadjusted beta of the target utility as a starting point because it results from the regression of the target utility's security returns relative to the market's returns. Thus, the resulting standard deviation of beta relates to the unadjusted beta. We use the standard deviation of the unadjusted beta to determine the range around it as the selection criterion based on systematic risk.

We use the residual standard error of the regression as a measure of unsystematic risk. The residual standard error reflects the extent to which events specific to the firm's operations affect a firm's stock price. Thus, it is a measure of diversifiable, unsystematic, firm-specific risk.

An Illustration of Authors' Approach

Step One: We begin our approach by establishing the selection criteria as a range of both unadjusted beta and residual standard error of the target gas

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pipeline company.

As shown in table 1, our target gas pipeline company has a Value Line unadjusted beta of 0.90, whose standard deviation is 0.1250. The selection criterion range of unadjusted beta is the unadjusted beta plus (+) and minus (-) three of its standard deviations. By using three standard deviations, 99.73 percent of the comparable unadjusted betas is captured.

Three standard deviations of the target utility's unadjusted beta equals 0.38 (0.1250 x 3 = 0.3750, rounded to 0.38) Consequently, the range of unadjusted betas to be used as a selection criteria is 0.52 - 1.28 (0.52 = 0.90 - 0.38) and (1.28 = 0.90 + 0.38).

Likewise, the selection criterion range of residual standard error equals the residual standard error plus (+) and minus (-) three of its standard deviations. The standard deviation of the residual standard error is defined as: $\sigma/\sqrt{2N}$.

As also shown in table 1, the target gas pipeline company has a residual standard error of 3.7867. According to the above formula, the standard deviation of the residual standard error would be 0.1664 (0.1664 = 3.7867/ $\sqrt{2(259)}$ = 3.7867/22.7596, where 259 = N, the number of weekly price change observations over a period of five years). Three standard deviations of the target utility's residual standard error would be 0.4992 (0.1664 x 3 = .4992). Consequently, the range of residual standard errors to be used as a selection criterion is 3.2875 - 4.2859 (3.2875 = 3.7867 - 0.4992) and (4.2859 = 3.7867 + 0.4992)

Step Two: The step one criteria are applied to Value Line's data base of nearly 4,000 firms for which Value Line derives unadjusted betas and residual standard errors on a weekly basis. All firms with unadjusted betas and residual standard errors within the criteria ranges are then selected

Step Three: In the regulatory ratemaking environment, authorized common equity return rates are applied to a book-value rate base. Thus, the earnings rates on book common equity, or net worth, of competitive, non-utility firms are highly relevant provided those firms are indeed comparable in total risk to the target gas pipeline. The use of the return rates of other utilities has no relevance because their allowed, and hence subsequently achieved, earnings rates are dependent upon the regulatory

table 1

Summary of the Comparable Earnings Analysis for the Proxy Group of 248 Non-Utility Companies Comparable in Total Risk to the Target Gas Pipeline Company[1]

	1	2	3	4	5	6	7	8
			residual	rate of return on net worth				
	adj. beta	unadj. beta	standard error	3-year average[2]	4-year average[2]	5-year average[2]	5-year projected[3]	
average for the proxy group of 248 non-utility companies comparable in total risk to the target gas pipeline company	0.97	0.92	3.7705					
target gas pipeline company	0.96	0.90[4]	3.7867					
median				11.7%	12.0%	12.6%	15.5%	
average of the median historical returns					12.1%			
conclusion[5]								13.8%

[1] The criteria for selection of the non-utility group was that the non-utility companies be domestic and included in *Value Line Investment Survey*. The non-utility group was selected based on an unadjusted beta range of 0.52 to 1.28 and a residual standard error range of 3.2875 to 4.2859.
[2] Ending 1992.
[3] 1996-1998/1997-1999.
[4] The average standard deviation of the target gas pipeline company's unadjusted beta is 0.1250.
[5] Equal weight given to both the average of the 3-, 4- and 5-year historical medians (12.1%) and 5-year projected median rate of return on net worth (15.5%). Thus, 13.8% = (12.1% + 15.5% / 2).
Source: Value Line Inc., March 15, 1994
Value Line Investment Survey

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process. Consequently, we believe all utilities must be eliminated to avoid circularity. Moreover, we believe non-domestic firms must be eliminated because their reporting methods differ significantly from U.S. firms.

Step Four: We then eliminated those firms for which Value Line does not publish a "Ratings & Report" in *Value Line Investment Survey* so that the historical and projected returns on net worth[6] are from a consistent source. We use historical returns on net worth for the most recent five years, as well as those projected three to five years into the future. We believe it is logical to evaluate both historical and projected return rates because it is reasonable to assume that investors avail themselves of both when they are available from widely disseminated information services, such as Value Line Inc. The use of Value Line's return rates on net worth understates the common equity return rates for two reasons. First, preferred stock is included in net worth. Second, the net worth return rates are as of the end of each period. Thus, the use of average common equity return rates would yield higher results.

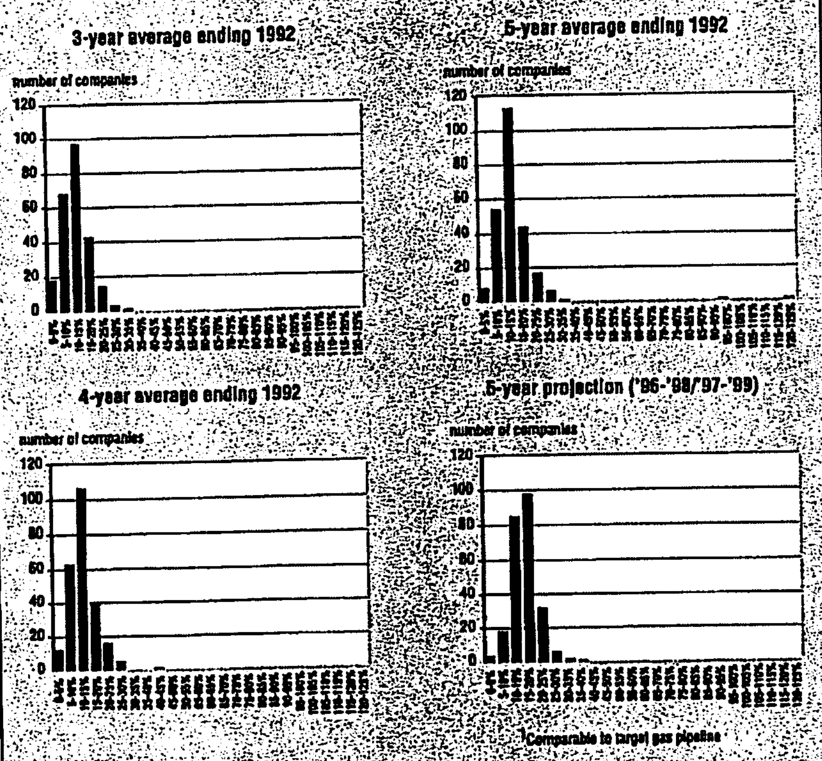
Step Five: Median returns based on the historical average three, four and five years ending 1992 and projected 1996-1998 or 1997-1999 rates of return on net worth are then determined as shown in columns 4 through 7 of table 1. The median is used due to the wide variations and skewness in rates of return on net worth for the non-utility firms as evidenced by the frequency distributions of those returns as shown in illustration 1.

However, we show the average unadjusted beta, 0.92, and residual standard error, 3.7705, for the proxy group in columns 2 and 3 of table 1 because their frequency distributions are not significantly skewed, as shown in illustration 2.

Step Six: Our conclusion of a com-

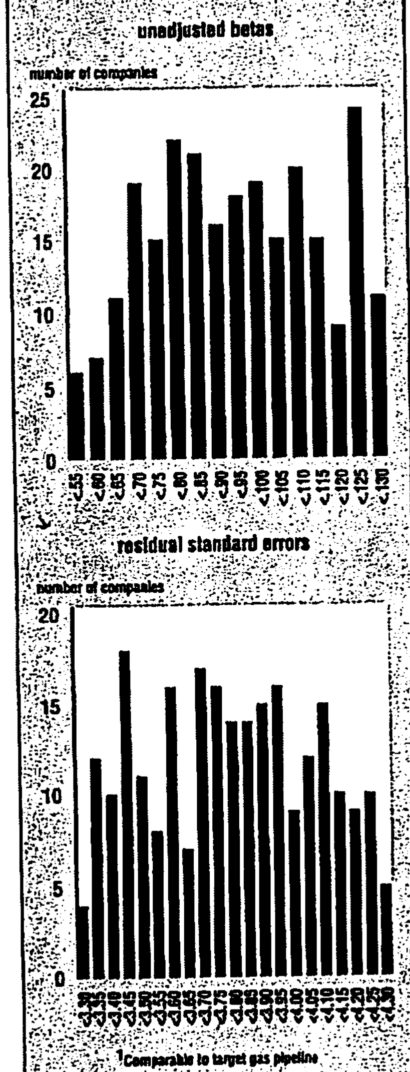
continued on page 8

Illustration 1
Rates of Return on Net Worth for the Proxy Group of 248 Non-Utility Companies[1]



[1]Comparable to target gas pipeline

Illustration 2
Unadjusted Betas and Residual Standard Errors for the Proxy Group of 248 Non-Utility Companies[1]



[1]Comparable to target gas pipeline

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parable earnings cost rate is based upon the mid-point of the average of the median three-, four- and five-year historical rates of return on net worth of 12.1 percent as shown in column 5 and the median projected 1996-1998/1997-1999 rate of return on net worth of 15.5 percent as shown in column 7 of table 1. As shown in column 8, it is 13.8 percent.

Summary

Our comparable earnings approach demonstrates that it is possible to select a proxy group of non-utility firms that is comparable in total risk to a target utility. In our example, the 13.8 percent comparable earnings cost rate is very conservative as it is an expected achieved rate on book common equity (a regulatory allowed rate should be greater) and because it is based on end-of-period net worth. A similar rate on average net worth would be about 20 to 40 basis points higher (i.e., 14.0 to 14.2 percent) and still understate the appropriate regulatory allowed rate of return on book common equity.

Our selection criteria are based upon measures of systematic and unsystematic risk, specifically unadjusted beta and residual standard error. They provide the basis for the objective selection of comparable non-utility firms. Our selection criteria rely on changes in market prices over approximately five years. We compare the aggregate total risk, or the sum of systematic and unsystematic risk, which reflects investors' aggregate assessment of both business and financial risk. Thus, no adjustments are necessary to the proxy group results to compensate for the differences in business risk and financial risk, such as accounting practices and debt/equity ratios. Moreover, it is inappropriate to attempt a comparison of the target utility with any individual firm, or subset of firms, in the proxy group because only the average firm of the group is relevant.

Because the comparable earnings model is firmly anchored in the "corresponding risk" precept established in the landmark court decisions, it is worthy of consideration as a principal model for use in estimating the cost rate of common equity capital of a regulated utility. Our approach to the comparable earnings model produces a proxy group that is indeed comparable in total risk because the selection process is objective and quantitative. It therefore overcomes criticism linked to arbitrary selection processes.

All cost-of-common-equity models, including the DCF and CAPM, are fraught with deficiencies, usually stemming from the many necessary but unrealistic assumptions that underlie them. The effects of the deficiencies of individual models can be mitigated by using more than one model when estimating a utility's common equity cost rate. Therefore, when the non-comparability issue is overcome, the comparable earnings model deserves to receive the same consideration as a primary model, as do the currently popular market-based models. ■

[1]*Bluefield Water Works Improvement Co. v. Public Service Commission*. 262 U.S. 679 (1922) and *Federal Power Commission v. Hope Natural Gas Co.* 320 U.S. 519 (1944)
[2]Charles F. Phillips Jr., The Regulation of Public Utilities: Theory and Practice, Public Utilities Reports Inc., 1988, p. 379
[3]James C. Bonbright, Albert L. Danielsen and David R. Kamerschen, Principles of Public Utilities Rates, 2nd edition, Public Utilities Reports Inc. 1988, p. 329
[4]Jack Clark Francis, Investments: Analysis and Management, 3rd edition, McGraw-Hill Book Co., 1980, p. 363
[5]Id., p. 548.
[6]Returns on net worth must be used when relying on Value Line data because returns on book common equity for non-utility firms are not available from Value Line

Report Lists Pipeline, Storage Projects

More than $9 billion worth of projects to expand the nation's natural gas pipeline network are in various stages of development, according to an A.G.A. report. These projects involve nearly 8,000 miles of new pipelines and capacity additions to existing lines and represent 15.3 billion cubic feet (Bcf) per day of new pipeline capacity.

During 1993 and early 1994, construction on 3,100 miles of pipeline was completed or under way, at a cost of nearly $4 billion, says A.G.A. These projects are adding 5.4 Bcf in daily delivery capacity nationwide.

Among the projects completed in 1993 were Pacific Gas Transmission Co.'s 805 miles of looping that allows increased deliveries of Canadian gas to the West Coast; Northwest Pipeline Corp.'s addition of 433 million cubic feet of daily capacity for customers in the Pacific Northwest and Rocky Mountain areas; and the 156-mile Empire State Pipeline in New York.

In addition, major construction projects were started on the systems of Texas Eastern Transmission Corp. and Algonquin Gas Transmission Co. — both subsidiaries of Panhandle Eastern Corp. — and along Florida Gas Transmission Co.'s pipeline.

The report goes on to discuss another $5 billion in proposed projects, which, if completed, will add nearly 5,000 miles of pipeline and 9.8 Bcf per day in capacity, much of it serving Florida and West Coast markets.

A.G.A. also identifies 47 storage projects and says that if all of them are built, existing storage capacity will increase by more than 500 Bcf, or 15 percent.

For a copy of *New Pipeline Construction: Status Report 1993-94* (#F00103), call A.G.A. at (703) 841-8490. Price per copy is $6 for employees of member companies and associates and $12 for other customers.

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THE COST OF CAPITAL –

A PRACTITIONER'S GUIDE

BY

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PREPARED FOR THE SOCIETY OF UTILITY AND REGULATORY FINANCIAL ANALYSTS (SURFA)

2010 EDITION

Author's Note: This manual has been prepared as an educational reference on cost of capital concepts. Its purpose is to describe a broad array of cost of capital models and techniques. No cost of equity model or other concept is recommended or emphasized, nor is any procedure for employing any model recommended. Furthermore, no opinions or preferences are expressed by either the author or the Society of Utility and Regulatory Financial Analysts.

TABLE 4.1
COMMON EQUITY RATIOS

Utility Group	Common Equity Ratio*
Electric Utilities	47%
Combination Electric & Gas Utilities	45%
Natural Gas Distribution & Integrated Natural Gas Companies	52%
Water Companies	46%

* Including short-term debt.

Source: AUS Utility Reports, September, 2010

Risk and Leverage

A general principle of finance maintains that the financing structure of a company should be determined in conjunction with the perceived risk of the assets. The obvious intuitive appeal of this principle goes back at least to Adam Smith (1776, 110-111) who stated:

> "...something must be given for the profits of the undertaker of the work who hazards his stock (capital) in this adventure... In all the different employments of stock, the ordinary rate of profit varies more or less with the certainty or uncertainty of the returns...the ordinary rate of profit always rises more or less with the risk."

Risk, in this context, can be segregated into two components - business risk and financial risk. Business risk refers to the risk inherent in the level and composition of a firm's assets, as well as the nature of the business in which the firm is engaged. In essence, business risk is reflected in the variability of the pre-tax operating income stream which the firm faces. A firm with a relatively low level of earnings variability is said to have low business risk while a firm with a relatively high level of earnings variability is said to have high business risk. Business risk is not related to the manner in which the firm finances its assets.

Financial risk refers to the capital structure of the firm and how this impacts the firm's after-tax net income and return on equity. Financial risk is created by the use of debt and preferred stock in the capital structure, which is called financial leverage. The use of leverage, or the use of fixed-cost financing with a (generally) lower cost than common equity, can have two impacts on a firm's return on equity. If the firm earns a return higher than the fixed-cost (i.e., leveraged) capital, the firm's return on equity is enhanced. However, if the firm earns a return lower than the fixed-cost capital, the firm's return on equity is reduced. In the extreme, financial leverage can result in bankruptcy if the firm's earnings do not cover its fixed-cost rates and sufficient cash (from prior periods) is not on hand to pay the required payments to the owners of the fixed-cost capital.

Capital Structure Issues

Several issues are encountered in the selection of a proper capital structure for ratemaking purposes.

Reconciling Rate Base and Capital Structure

As noted in Chapter 2, the rate base - rate of return concept is based on the recognition that rate base (assets) are financed with the capital structure (liabilities and equity). An inherent assumption of this concept is that the rate base and capital structure are equal in size. In reality, this assumption is not always true.

Cicchetti (1985, 41) has observed "The reconciliation of the rate base and the capital structure is an integral, and often overlooked, segment of determining the required overall rate of return". Rate base and capitalization may differ for a number of reasons, including the existence of non-utility assets and the regulatory disallowance of certain assets.

One method for reconciling rate base and capital structure is known as the "balance sheet method". This methodology begins with defining the usual rate base items (net plant in service, property held for future use, construction work in progress, and working capital) and then equating this with the capital structure items financing the rate base. As adjustments are made to remove

CERTIFICATE OF SERVICE

The undersigned employee of Elliott & Elliott, P.A. does hereby certify that she has served below listed parties with a copy of the pleading(s) indicated below by mailing a copy of same to them in the United States mail, by regular mail, with sufficient postage affixed thereto and return address clearly marked on the date indicated below:

RE: Application of Carolina Water Service, Inc. for adjustment of rates and charges and modification of certain terms and conditions for the provision of water and sewer service

DOCKET NO.: 2011-47-WS

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PLEADING: Omitted Exhibit to Rebuttal Testimony of Pauline M. Ahern

August 29, 2011

Jackie C. Livingston

Jackie C. Livingston, Paralegal